

**HOW WELL DO HUNGER AND SATIETY RATINGS PREDICT THE  
AMOUNT CONSUMED AT A MEAL?**

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

Colten Anthony Morace

August 2019

© 2019 Colten Anthony Morace

## ABSTRACT

While the subjective measures of hunger and satiety are often used in the context of appetite research, their correlations with food intake seem to vary substantially, ranging from tenuous to moderate. The purpose of the present study was to utilize multilevel mixed models with marginal and conditional correlation coefficients to quantify the relationship between (a) the perception of pre-meal hunger and subsequent intake, (b) the change in hunger across a meal and the amount consumed, (c) the perception of satiety following a meal and the amount consumed at that meal, and (d) the change in satiety across a meal and the amount consumed while accounting for between subject and within subject variability. One hundred fourteen participants were asked to self-report on hunger and satiety before and after lunch and dinner via monopolar numerical rating scales as well as record the weight of each meal via portable scales on three different days. The average consumption per meal was 359 grams (95% CI [328, 390]). Gender had a significant effect on consumption ( $p = 0.001$ ) as males consumed a mean of 436 grams (95% CI [384, 488]) compared to females (323 grams, 95% CI [287, 359]). Meal also had a significant effect on consumption ( $p = 0.007$ ) as participants consumed more at dinner (393 grams, 95% CI [359, 426]) compared to lunch (325 grams, 95% CI [291, 359]). When accounting for the random effect of participant ID, which factored in between subject and within subject variability, our multilevel mixed-effects models explained 50-55% of the variability observed in consumption and displayed significant effects on intake for gender ( $p = 0.0011$ ), meal ( $p < 0.0001$ ), pre-hunger ( $p < 0.0001$ ), change in hunger

( $p < 0.0001$ ), pre-satiety ( $p = 0.0005$ ), and change in satiety ( $p < 0.0001$ ); however, when not accounting for the random effect of participant ID, the models could only account for 4-9% of the variability observed in consumption. Between subject variability contributed to approximately 45% of the random effect of participant ID, whereas within subject variability contributed roughly 55%. This suggests that when only accounting for between subject variability, the predictive power of hunger and satiety on intake in our models would have been somewhat limited. It is likely that our models captured a number of factors affecting within subject variation to some degree. Without being able to measure and disentangle their effects on intake, it is difficult to discern the true effects of hunger and satiety on consumption. As it stands, when accounting for between and within subject variability, hunger and satiety were moderately predictive of food intake in our sample.

## BIOGRAPHICAL SKETCH

Colten Morace, a native of Longview, Texas, received his Associate of Science degree from Kilgore College in 2014 before transferring to Texas State University after being rewarded a Terry Transfer Scholarship from the Terry Foundation. There he received his Bachelor of Science (*summa cum laude*) in Dietetics in 2017. Afterwards, he began studying the control of food intake in humans at Cornell University, graduating with his Master of Science in Nutritional Sciences in 2019.

I would like to dedicate this thesis to my late father, Russell Burks. You masterfully instructed me in the ways of life, as a parent, a mentor, and a friend. Your love, motivation, and encouragement paved the path that I have and continue to walk. It was, is, and will always be an honor to have shared the time that we had together.

## ACKNOWLEDGMENTS

To my advisor, David Levitsky, I am grateful for the guidance he provided me during my graduate studies as well as his understanding patience, contagious enthusiasm, and immense knowledge.

I would also like to sincerely thank Barbara Strupp for serving on my committee and offering consistent encouragement and kind support throughout my research.

In addition, a thank you to Francoise Vermeulen, Lynn Johnson, and Erika Mudrak at the Cornell Statistical Consulting Unit for their assistance with the statistical analysis of this thesis.

Moreover, I am grateful for my Division of Nutritional Sciences friends, with a special acknowledgement for Yuuki Nakayachi for his relentless encouragement.

Lastly, I would like to thank my friends and family, especially my mother, Wendy Burks, back home in Texas for their loving support.

## TABLE OF CONTENTS

BIOGRAPHICAL SKETCH.....	iii
DEDICATION.....	iv
ACKNOWLEDGEMENTS.....	v
TABLE OF CONTENTS.....	vi
LIST OF FIGURES.....	vii
LIST OF TABLES.....	viii
INTRODUCTION.....	1
METHODS.....	3
RESULTS.....	6
DISCUSSION.....	13
REFERENCES.....	19
APPENDIX.....	25



## LIST OF FIGURES

<b>Figure 1.</b> Experimental workflow of data collection.....	4
<b>Figure 2.</b> Mean amount consumed as a function of gender controlling for the random effect of participant ID.....	6
<b>Figure 3.</b> Mean amount consumed as a function of meal controlling for the random effect of participant ID.....	7
<b>Figure 4.</b> Mean amount consumed as a function of day controlling for the random effect of participant ID.....	8
<b>Figure 5.</b> Mean amount consumed as a function of age controlling for the random effect of participant ID.....	9
<b>Figure 6.</b> Scatterplot matrix of predictors.....	10

## LIST OF TABLES

<b>Table 1.</b> Summary of model fixed effects parameter estimates .....	12
--	----

## INTRODUCTION

A recent Pubmed search (June 29, 2019) of the medical literature revealed 6,042 studies that contained the word “hunger” and 12,410 studies that used the word “satiety”. Indeed, such terms are commonly used in the context of appetite research to explain why humans consume and terminate a given meal.

Implicit in these types of studies is the idea that eating behavior is driven by hunger and satiety. If this were the case, then a high correlation should exist between pre-meal hunger and/or change in hunger across a meal and the amount consumed at that meal. Likewise, satiety after the meal and/or changes in satiety across a meal should correlate highly with the amount consumed.

While it has been common practice to utilize these subjective measures in appetite research, hunger and satiety ratings often fail to correlate with energy intake.<sup>1-9</sup> When they do, such correlations vary substantially, ranging from tenuous to moderate.<sup>10-13</sup> Furthermore, few studies have investigated the efficacy of using such measures for the study of food intake in humans.<sup>14-16</sup> In a recent review, it was found that only 6 out of 39 reports found consistent, statistically significant correlations between appetitive sensations and intake.<sup>16</sup> In one such study, while a moderate correlation between hunger and food intake within the same hour was observed with

group data ( $r = 0.50$ ,  $p < 0.02$ ), the relationship was weak across individuals with correlations ranging from 0.002 to 0.38.<sup>15</sup>

The purpose of the present study was to utilize multilevel mixed models with marginal and conditional correlation coefficients to quantify the relationship between (a) the perception of pre-meal hunger and subsequent intake, (b) the change in hunger across a meal and the amount consumed, (c) the perception of satiety following a meal and the amount consumed at that meal, and (d) the change in satiety across a meal and the amount consumed while accounting for between subject and within subject variability.

## METHODS

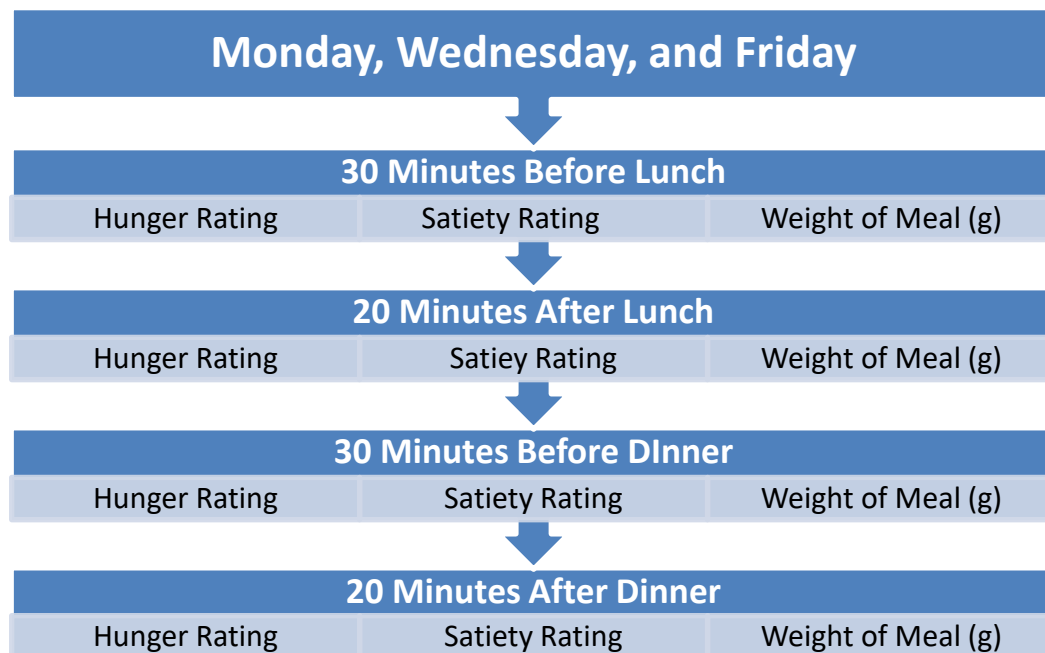
### *Subjects*

One hundred fourteen students, aged 19-26 years, were recruited through a Cornell University undergraduate course and received extra credit for participating. The study was approved by Cornell University's Institutional Review Board (IRB) for Human Participants.

### *Protocol*

After initial recruitment, participants attended a study briefing during which the purpose of the experiment was explained and a written informed consent was given. Information regarding age, gender, cell phone number, and approximate mealtimes for lunch and dinner over the next week was collected. In addition, each of the subjects received a small, portable scale (Joseph Joseph 40071 Tri Scale) and were given a demonstration of its use. Beginning a week following the briefing, participants were asked to self-report on hunger and fullness (satiety) before and after lunch and dinner on three different days (Monday, Wednesday, and Friday) via monopolar numerical ratings scales (Appendix A1). For each meal, all rating scales and responses were communicated through text messages. Hunger and satiety were presented on these scales as ratings from 1 to 7 with anchors at each endpoint such that 1 represented feeling not hungry/not satiated at all and 7 represented feeling extremely hungry/extremely satiated. The subjects were also asked to report the weight of each meal being recorded in grams before and after consumption during this week using the

portable scales. For each test meal, participants were sent a reminder text message 30 minutes prior to their designated mealtime and allowed up to two hours to respond with their initial pre-meal weight, hunger rating, and satiety rating. Twenty minutes after receiving the initial pre-meal responses, researchers sent a follow-up text to collect post-meal responses. Participants were again given up to two hours to respond with their post-meal weight, hunger rating, and satiety rating. If the participants failed to respond to the initial post-meal message, they were sent another notification asking them to do so. If no response was received, the meal was omitted from analysis. The experimental workflow during data collection is depicted in Figure 1. Following data collection, the participants attended a study debriefing where the portable scales were collected and remaining questions concerning the study were addressed.



**Figure 1.** Experimental workflow of data collection.

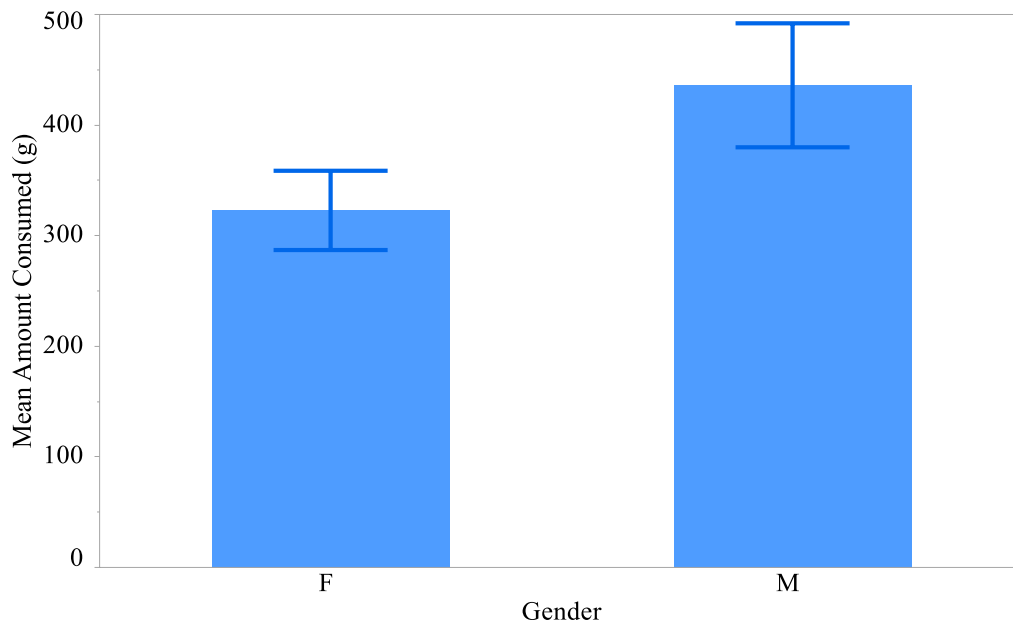
### *Statistical analysis*

The study followed a within-subjects experimental design. For each participant, changes in hunger and satiety ratings were calculated for every meal as the difference between pre and post meal ratings, and consumption was calculated as the difference between pre and post meal weights. Univariate and bivariate analyses, including multivariate correlations, were performed. Multilevel linear regression was used to investigate the strength of the relationships between consumption and changes in hunger or satiety controlling for age, gender, meal, and day. To describe the amount of variance in consumption explained by both fixed and random factors in our mixed models, marginal and conditional  $r^2$  values, as described by Nakagawa and Schielzeth, were calculated.<sup>17</sup> A two-tailed level  $p < 0.05$  was set as the criterion for significance. All calculations were performed using JMP Pro (version 14.0.0) and RStudio (version 3.6.0) for Windows 10.

## RESULTS

A total of 677 meals were recorded. Twenty-four meals were removed from analysis due to incomplete data. The sample included 36 males and 78 females, and the average consumption per meal was 359 grams (95% CI [328, 390]).

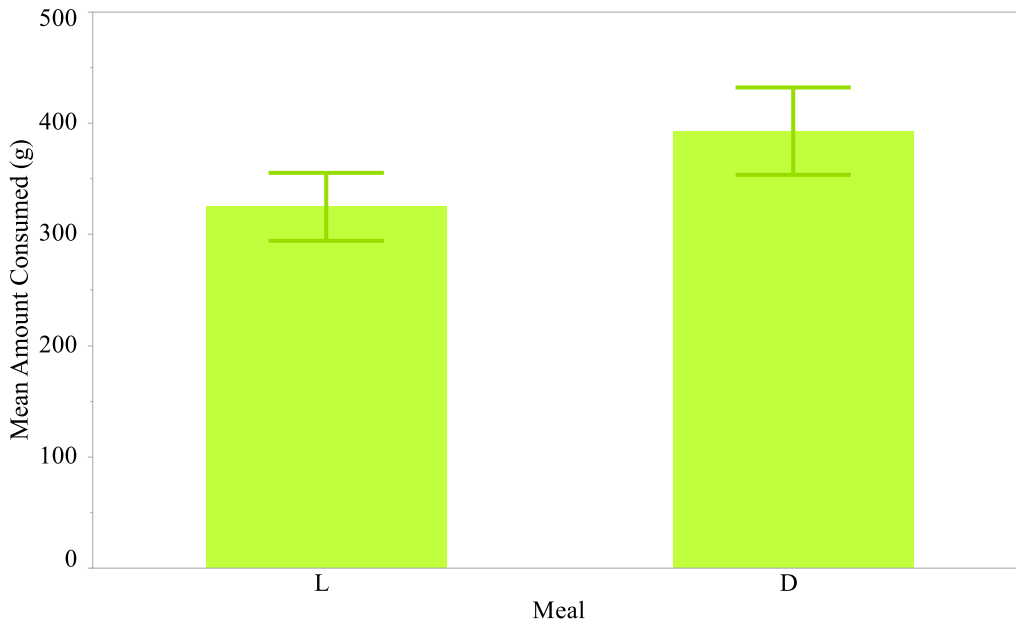
As seen in Figure 2, gender had a significant effect on consumption ( $p = 0.001$ ) as males consumed a mean of 436 grams (95% CI [384, 488]) compared to females (323 grams, 95% CI [287, 359]).



**Figure 2.** Mean amount consumed as a function of gender controlling for the random effect of participant ID. Each error bar was constructed using a 95% confidence interval of the mean

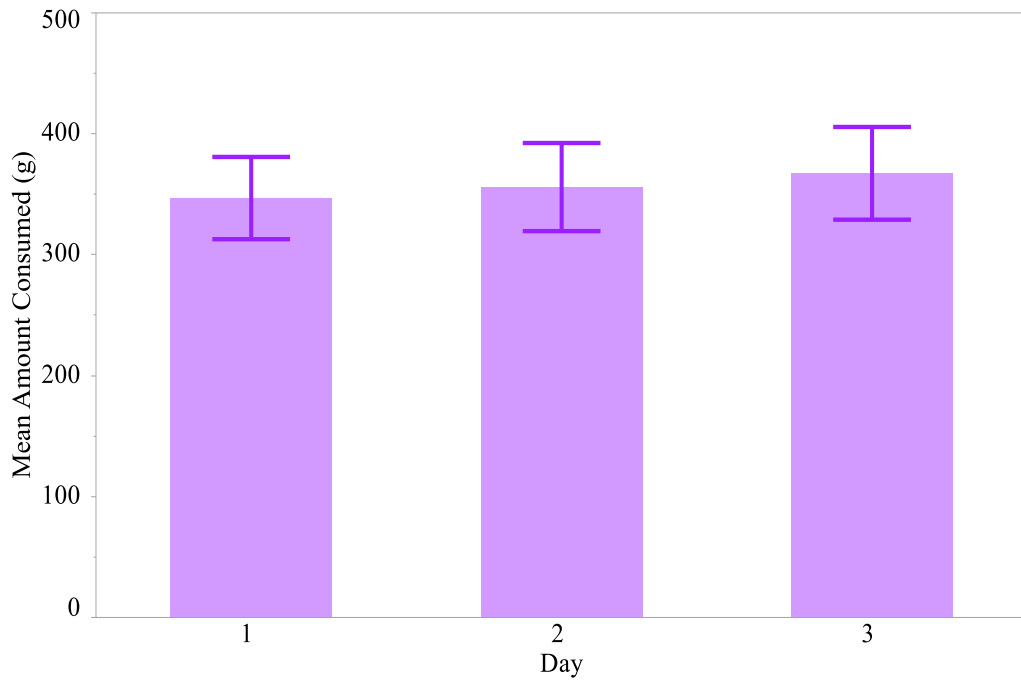


Meal also had a significant effect on consumption ( $p = 0.007$ ) as participants consumed more at dinner (393 grams, 95% CI [359, 426]) compared to lunch (325 grams, 95% CI [291, 359], Figure 3).

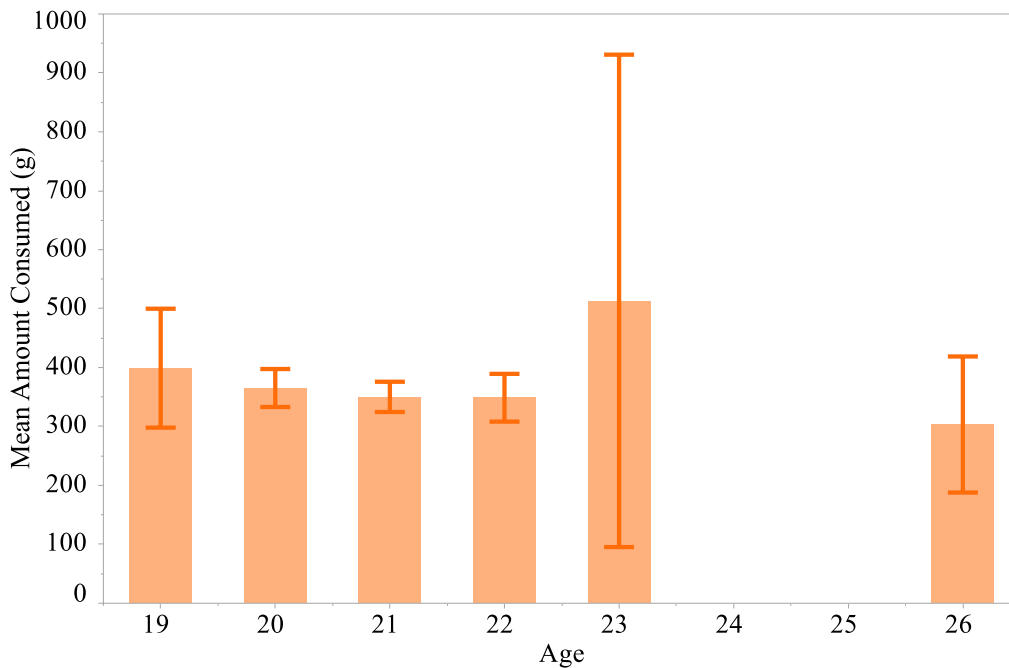


**Figure 3.** Mean amount consumed as a function of meal controlling for the random effect of participant ID. Each error bar was constructed using a 95% confidence interval of the mean.

In addition, the day on which the test meals were consumed did not have a significant effect on consumption; however, participants did consume more per meal as the week of data collection progressed, with an mean of 347 grams (95% CI [311, 383]) per meal on the first day, 356 grams (95% CI [320, 392]) per meal on the second day, and 366 grams (95% CI [330, 402]) per meal on the third day (Figure 4). No relationship was observed between consumption and age (range 303 to 513 grams, Figure 5).

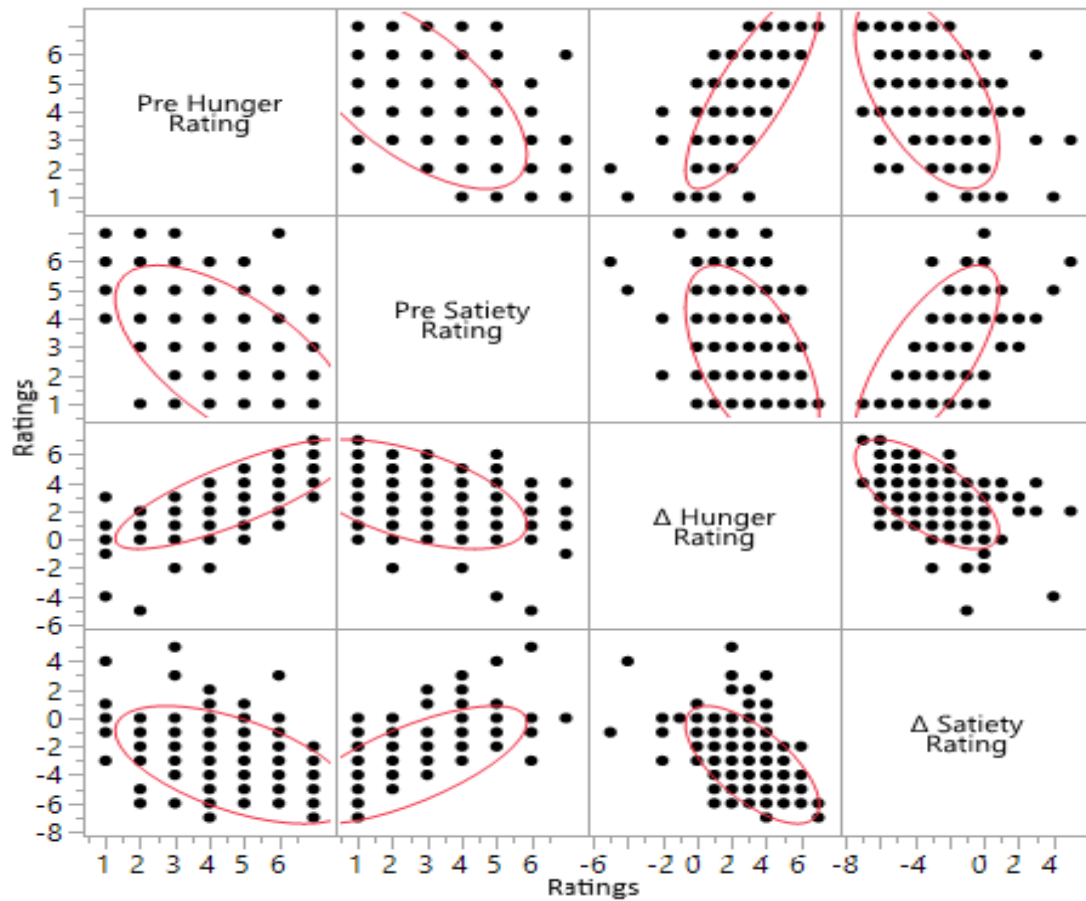


**Figure 4.** Mean amount consumed as a function of day controlling for the random effect of participant ID. Each error bar was constructed using a 95% confidence interval of the mean.



**Figure 5.** Mean amount consumed as a function of age controlling for the random effect of participant ID. Each error bar was constructed using a 95% confidence interval of the mean.

Pre-hunger rating was highly positively correlated with  $\Delta$  hunger rating ( $r = 0.81, p < 0.0001$ ) as well as negatively correlated with pre-satiety rating ( $r = -0.65, p < 0.0001$ ) and  $\Delta$  satiety rating ( $r = -0.58, p < 0.0001$ ), as seen in Figure 6. Likewise, pre-satiety was found to be highly positively correlated with  $\Delta$  satiety rating ( $r = 0.72, p < 0.0001$ ) as well as negatively correlated with pre hunger rating ( $r = -0.65, p < 0.0001$ ) and  $\Delta$  hunger rating ( $r = -0.55, p < 0.0001$ , Figure 6). Because of these high correlations, separate models for pre-hunger rating,  $\Delta$  hunger rating, pre-satiety rating, and  $\Delta$  satiety rating were used. A summary of the fixed effects parameter estimates for each model can be seen in Table 1.



**Figure 6.** Scatterplot matrix of pre hunger rating in the first row, pre satiety rating in the second row,  $\Delta$  hunger rating in the third row, and  $\Delta$  satiety rating in the fourth row.

In model 1 with the fixed effects of gender, age, meal, day, and pre-hunger rating and the random effect of participant ID, significant effects on consumption were observed for gender ( $\beta = -111.12$ ,  $t(110) = -3.34$ ,  $p = 0.0011$ ), meal ( $\beta = 63.27$ ,  $t(516) = 4.76$ ,  $p < 0.0001$ ), and pre hunger rating ( $\beta = 31.06$ ,  $t(87) = 5.63$ ,  $p < 0.0001$ ). The conditional and marginal correlation coefficients for this model were 0.50 and 0.06, respectively.

A similar pattern was seen in model 2 with the fixed effects of gender, age, meal, day, and  $\Delta$  hunger rating and the random effect of participant ID. Significant effects on consumption were observed for gender ( $\beta = -97.05$ ,  $t(115) = -2.99$ ,  $p = 0.0034$ ), meal ( $\beta = 62.29$ ,  $t(533) = 4.84$ ,  $p < 0.0001$ ), and  $\Delta$  hunger ( $\beta = 38.07$ ,  $t(77) = 7.56$ ,  $p < 0.0001$ ). The conditional and marginal correlation coefficients for this model were 0.55 and 0.09, respectively.

Likewise, in model 3 with the fixed effects of gender, age, meal, day, and pre satiety rating and the random effect of participant ID, significant effects on consumption were observed for gender ( $\beta = -116.87$ ,  $t(110) = -3.54$ ,  $p = 0.0006$ ), meal ( $\beta = 66.72$ ,  $t(539) = 5.00$ ,  $p < 0.0001$ ), and pre satiety rating ( $\beta = -25.69$ ,  $t(90) = -3.62$ ,  $p = 0.0005$ ). The conditional and marginal correlation coefficients for this model were 0.52 and 0.04, respectively.

Lastly, in model 4 with the fixed effects of gender, age, meal, day, and  $\Delta$  satiety and the random effect of participant ID, significant effects on consumption were observed for gender ( $\beta = -102.78$ ,  $t(112) = -3.02$ ,  $p = 0.0031$ ), meal ( $\beta = 62.39$ ,  $t(535) = 4.80$ ,  $p < 0.0001$ ), and  $\Delta$  satiety ( $\beta = -34.7$ ,  $t(81) = -6.79$ ,  $p < 0.0001$ ). The conditional and marginal correlation coefficients for this model were 0.55 and 0.08, respectively.

**Table 1. Summary of Model Fixed Effects Parameter Estimates with Consumption as Response Variable**

Predictors	Model 1	Model 2	Model 3	Model 4
Intercept	410 (-241, 106)	310 (-317, 937)	629 (-11, 1269)	485 (-166, 1137)
Gender [F] <sup>a</sup>	-111 (-177, -45)**	-97 (-161, -33)**	-117 (-182, -51)**	-103 (-170, -35)**
Age	8 (-39, 23)	-2 (-32, 28)	-8 (-39, 22)	-10 (-41, 21)
Day [2] <sup>b</sup>	9 (-23, 40)	13 (-18, 43)	2 (-29, 34)	8 (-23, 38)
Day [3] <sup>b</sup>	24 (-8, 56)	23 (-9, 54)	23 (-9, 56)	23 (-9, 54)
Meal [D] <sup>c</sup>	63 (37, 89)***	62 (37, 88)***	67 (41, 93)***	62 (37, 88)***
Pre-Hunger	31 (20, 42)***	-	-	-
Δ Hunger	-	38 (28, 48)***	-	-
Pre-Satiety	-	-	-26 (-40, -12)**	-
Δ Satiety	-	-	-	-35 (-45, -25)***

<sup>a</sup> The reference value for the nominal variable 'Gender' is male [M]. <sup>b</sup> The reference value for the nominal variable 'Day' is [1]. <sup>c</sup> The reference value for the nominal variable 'Meal' is lunch [L].

\*\* P < 0.01, \*\*\* P < 0.0001. Note: confidence intervals are at a level of 0.95. Parameter estimates are in grams of consumption.

## DISCUSSION

Utilizing multilevel mixed-effects models for the investigation of the strength of relationships between consumption and hunger as well as satiety allowed for differences between and within groups, or individuals in this case, to be modelled as a random effect. In this way, the random effect was a proxy for individual variation in the sample captured by the models. The conditional  $r^2$  describes the proportion of variance explained by both fixed and random effects, whereas the marginal  $r^2$  describes the proportion of variance explained by fixed effects alone.<sup>17</sup> Analysis of the linear mixed model for pre-hunger rating revealed a significant linear relationship between pre-hunger rating and the amount consumed at a meal. Such a relationship could explain approximately 50% of the variation in meal intake when also accounting for the fixed effects of gender, age, meal, and day as well as the random effect of the subjects. However, when the random effect of participant ID was removed from the equation, the amount of variance in consumption that could be accounted for by the model was reduced to 6%. Similarly, change in hunger ratings across the meal could account for approximately 55% of the variance in consumption. When the random effect of participant ID was removed, the percentage of variance in the amount consumed that could be accounted for by the model was reduced to 9%.

Measures of satiety show similar effects. The linear mixed model for pre-satiety could explain 52% of the variability observed in consumption, but when the random effect of the subjects was removed, the model could account for only 4% of the

variability observed in consumption. Change in satiety showed a similar pattern. When accounting for the random effect of participant ID, the mixed linear model for change in satiety could account for 55% of the variability in consumption, but the same model could account for only 8% of the variability observed in consumption when not accounting for subject variability.

Another way of viewing the significance of these findings is that for every unit increase in pre-meal hunger, we would expect an increase in consumption of approximately 30 grams. Likewise, for every unit change in hunger across a meal, consumption would be expected to change conversely by about 38 grams. A similar pattern is observed for satiety, where a one unit increase in pre-meal satiety would be expected to decrease consumption by approximately 26 grams. Moreover, for every unit change in satiety across a meal, we would expect an inverse change in consumption of about 35 grams. By themselves, each of these changes only accounts for approximately 10% of the mean overall consumption at a meal (359 grams); however, when considered with the fact that the average change in each of these measures was 2-3 units per meal, these findings become much more relevant, possibly contributing to up to 30% of consumption at a meal when also accounting for the random effect of participant ID. In addition, both gender and meal showed significant effects on consumption in our bivariate analyses as well as our multilevel linear regression modeling, approximately 100 and 60 grams, respectively, when accounting for between and within subject variation.



With that said, between subject variability contributed to approximately 45% of the random effect of participant ID, whereas within subject variability contributed roughly 55%. When considering the disparity between the marginal and conditional correlation coefficients observed across our models, which was caused by the random effect of participant ID, and the contribution of each type of subject variability to that random effect, it would seem the predictive power of hunger and satiety as well as gender and meal on intake in our models would have been somewhat limited when only accounting for between subject variability.

A number of factors at the individual level have been found to affect food intake over the years, such as age, gender, ethnicity, physical activity, body mass index (BMI), education, alcohol consumption, and smoking status.<sup>18-28</sup> More subtle factors, including mood, hedonic preferences and eating restraint, have also been implicated in affecting the consumption of food in humans.<sup>29-35</sup> To compound the matter, the satiating effect of foods as a function of fiber and macronutrient composition have also been found to modulate food intake, in addition to environmental factors not immediately associated with the individual, such as food portion size and social facilitation of eating.<sup>36-42</sup> Even though gender and age were the only two individual characteristics recorded for our sample, we were still able to capture the effect on consumption of various factors associated with between subject variability, such as those mentioned above. What remains to be seen, however, is how much these factors affected within subject variability, which was associated with over half of the variance in our response attributable to the random effect of participant ID.

This study had several strengths. Although we were unable to identify exactly which individual characteristics affected consumption to such a great degree, using multilevel mixed models with a random effect for participant ID was a strength of the study. Doing so allowed us to capture the effect of individual variability within our sample on food intake. Utilizing conditional and marginal correlation coefficients was another strength of the study. Since mixed models yield a variance for the residuals as well as variances associated with each random factor, calculating a correlation coefficient relative to only the residual variance, like what is done in least squares regression, would be inappropriate. The conditional correlation coefficient addresses this by factoring in variance associated with random effects, and when used with a marginal correlation coefficient, allow for the visualization of the effects of random factors on a linear relationship.<sup>17</sup> Duration of a study is another important consideration when investigating food intake as any effects observed at one meal, known as the acute food intake model, might be transient in nature.<sup>43</sup> Collecting data for multiple meals a day over the course of a week was a strength as it allowed for the capture of effects on intake that would not have been detected in a single meal study. There is ample evidence in the literature that demonstrates the significant impact that positive food primes in our environment, such as advertising, portion size, and social facilitation, can have on food intake in humans.<sup>39-42</sup> Using weighted intakes in a free-living situation allowed for the capture of these effects on consumption, giving the study external validity.

While the study did possess external validity, such research often lacks the interval validity of experiments performed in controlled laboratories. Studies performed in free-living situations struggle from a number of methodological problems, specifically with data collection, as participants often under report intake.<sup>43</sup> In addition to reporting bias, this study suffered from the fact that there were various other factors outside of the participants that could have contributed to the individual variation captured in our models. Unfortunately, it is impossible to control for such effects in a study on intake in a free-living situation such as this one. Furthermore, hunger and satiety ratings were only collected a half hour before and twenty minutes after each meal. Any effects possibly operating on these measures outside of this window were not detected. As such, the correlations captured by this study might be providing a restricted view of the true relationship between consumption and hunger as well as satiety. Lastly, although previous studies have revealed little difference between numerical category and line scales, they do possess weaknesses worth mentioning. First, category scales fall prey to a regression effect where subjects avoid marking end categories for fear that they will be unable to record more intense feelings afterwards. This reduces the number of points on the scale being used and ultimately, statistical results derived from them. In addition, unlike labeled magnitude scales, category scales are not ratio scales. In other words, a hunger rating of 4 on a numerical category scale is not necessarily twice the intensity of a hunger rating of 2. Furthermore, one cannot conclude that the sensations associated with the distance between 1 and 2 on this type of scale are the same as the distance between 6 and 7, as interpretations of these subjective feelings will most likely differ among subjects.

These weaknesses limit the mathematical level of the data, which ultimately affects the conclusions that can be drawn from them.<sup>43, 44-46</sup>

Attempting to correlate subjective measures such as hunger and satiety with an objective measure like that of food intake assumes that individuals perceive these sensations to the same degree, which is most likely not the case. Confounding the matter is the fact that different scales of varying specificity and sensitivity are often used to measure these appetitive sensations. Moreover, differences in methodology and statistical analyses yield potentially incomplete or skewed relationships between these subjective measures and consumption. Despite weak to moderate correlations between food intake and appetitive sensations, it is often posited that hunger and satiety are determinants of food intake. One could argue that if these subjective measures drove intake, much higher correlations would exist. A potential reason for this discrepancy is the possibility that the relationship between subjective sensations and consumption might be more complex, often affected to varying degrees by external factors which might not be measurable in certain experimental designs. It is likely that our models captured a number of factors affecting within subject variation to some degree. Without being able to measure and disentangle their effects on intake, it is difficult to discern the true effects of hunger and satiety on consumption. As it stands, when accounting for between and within subject variability, hunger and satiety were moderately predictive of food intake in our sample.

## REFERENCES

1. Pi-Sunyer X, Kissileff HR, Thornton J, Smith GP. C-Terminal octapeptide of cholecystokinin decreases food intake in obese men. *Physiol Behav.* 1982; 29(4):627–30.
2. Thompson DA, Welle SL, Lilavivat U, Penicaud L, Campbell RG. Opiate receptor blockade in man reduces 2-Deoxy-D-Glucose-induced food intake but not hunger, thirst, and hypothermia. *Life Sci.* 1982; 31(8):847–52.
3. Trenchard E, Silverstone T. Naloxone reduces the food intake of normal human volunteers. *Appetite.* 1983; 4(1):43–50.
4. Hrboticky N, Leiter LA, Anderson GH. Effects of L-tryptophan on short term food intake in lean men. *Nutr Res.* 1985; 5(6):595–607.
5. de Castro JM, Elmore DK. Subjective hunger relationships with meal patterns in the spontaneous feeding behavior of humans: Evidence for a causal connection. *Physiol Behav.* 1988; 43(2):159–65.
6. Rolls BJ, Hetherington M, Laster LJ. Comparison of the effects of aspartame and sucrose on appetite and food intake. *Appetite.* 1988; 11:62–7.
7. Rogers PJ, Blundell JE. Uncoupling sweet taste and calories effects of saccharin on hunger and food intake in human subjects. *Ann N Y Acad Sci.* 1989; 575(1):569–71.
8. Parker BA, Sturm K, MacIntosh CG, Feinle C, Horowitz M, Chapman IM. Relation between food intake and visual analogue scale ratings of appetite and

- other sensation in healthy older and young subjects. *Eur J Clin Nutr.* 2004; 58(2):212–8.
9. McKiernan F, Hollis JH, McCabe GP, Mattes RD. Thirst-drinking, hunger-eating; Tight coupling? *J Am Diet Assoc.* 2009; 109(3):486–90.
  10. Spiegel TA, Stunkard AJ, Shrager EE, O'Brien CP, Morrison MF, Stellar E. Effect of naltrexone on food intake, hunger, and satiety in obese men. *Physiol Behav.* 1987; 40(2):135–41.
  11. Wolkowitz OM, Doran AR, Cohen MR, Cohen RM, Wise TN, Pickar D. Single-dose naloxone acutely reduces eating in obese humans: Behavioral and biochemical effects. *Biol Psychiatry.* 1988; 24(4):483–7.
  12. Flint A, Raben A, Blundell J, Astrup A. Reproducibility, power and validity of visual analogue scales in assessment of appetite sensations in single test meal studies. *Int J Obes.* 2000;24(1):38–48.
  13. Parker BA, Ludher AK, Khai Loon T, Horowitz M, Chapman IM. Relationships of ratings of appetite to food intake in healthy older men and women. *Appetite.* 2004; 43(3):227–33.
  14. Mattes R. Hunger ratings are not a valid proxy measure of reported food intake in humans. *Appetite.* 1990;15(2):103–13.
  15. Mattes RD, Hollis J, Hayes D, Stunkard AJ. Appetite: Measurement and manipulation misgivings. *J Am Diet Assoc.* 2005;105(5 SUPPL.):87–97.
  16. McKiernan F, Houchins JA, Mattes RD. Relationships between human thirst, hunger, drinking, and feeding. *Physiol Behav.* 2008; 94(5):700–8.

17. Nakagawa S, Schielzeth H. A general and simple method for obtaining R<sup>2</sup> from generalized linear mixed-effects models. *Methods Ecol Evol.* 2013; 4(2):133–42.
18. Monella LF, Mayer J. Hunger and satiety in men, women, boys, and girls. *Am J Clin Nutr.* 1967; 20(3):253–61.
19. Wurtman JJ, Lieberman H, Tsay R, Nader T, Chew B. Calorie and nutrient intakes of elderly and young subjects measured under identical conditions. *J Gerontol Biol Sci.* 1988; 43(6):174–80.
20. Parker BA, Sturm K, MacIntosh CG, Feinle C, Horowitz M, Chapman IM. Relation between food intake and visual analogue scale ratings of appetite and other sensation in healthy older and young subjects. *Eur J Clin Nutr.* 2004; 58(2):212–8.
21. Johansson G, Wikman Å, Åhrén A-M, Hallmans G, Johansson I. Underreporting of energy intake in repeated 24-hour recalls related to gender, age, weight status, day of interview, educational level, reported food intake, smoking habits and area of living. *Public Health Nutr.* 2001; 4(4):919–27.
22. Rolls BJ, Kim-Harris S, Fischman MW, Foltin RW, Moran TH, Stoner SA. Satiety after preloads with different amounts of fat and carbohydrate: implications for obesity. *Am J Clin Nutr.* 1994; 60:476–87.
23. Legg C, Puri A, Thomas N. Dietary restraint and self-reported meal sizes: Diary studies with differentially informed consent. *Appetite.* 2000; 34(3):235–43.

24. Manz K, Mensink GBM, Finger JD, Haftenberger M, Brettschneider AK, Barbosa CL, et al. Associations between physical activity and food intake among children and adolescents: Results of KIGGS wave 2. *Nutrients*. 2019; 11(5).
25. Schrieks IC, Stafleu A, Griffioen-Roose S, de Graaf C, Witkamp RF, Boerrigter-Rijneveld R, et al. Moderate alcohol consumption stimulates food intake and food reward of savoury foods. *Appetite*. 2015; 89:77–83.
26. Yeomans MR, Caton S, Hetherington MM. Alcohol and food intake. *Curr Opin Clin Nutr Metab Care*. 2003; 6(6):639–44.
27. Eicher-Miller HA, Fulgoni VL, Keast DR. Processed food contributions to energy and nutrient intake differ among US children by race/ethnicity. *Nutrients*. 2015; 7(12):10076–88.
28. Di Noia J, Monica D, Cullen KW, Pérez-Escamilla R, Gray HL, Sikorskii A. Differences in fruit and vegetable intake by race/ethnicity and by hispanic origin and nativity among women in the Special Supplemental Nutrition Program for Women, Infants, and Children, 2015. *Prev Chronic Dis*. 2016; 13(2):1–13.
29. Castro DE. Macronutrient relationships with meal patterns and mood in the spontaneous feeding behavior of humans. *Physiology Behav*. 1987; 39:561–9.
30. De Castro JM, McCormick J, Pedersen M, Kreitzman SN. Spontaneous human meal patterns are related to preprandial factors regardless of natural environmental constraints. *Physiol Behav*. 1986; 38(1):25–9.



31. Lowe MR, Butryn ML. Hedonic hunger: A new dimension of appetite? *Physiol Behav.* 2007; 91(4):432–9.
32. Sorensen LB, Moller P, Flint A, Martens M, Raben A. Effect of sensory perception of foods on appetite and food intake: A review of studies on humans. *Int J Obes.* 2003; 27(10):1152–66.
33. Yeomans MR, Gray RW, Mitchell CJ, True S. Independent effects of palatability and within-meal pauses on intake and appetite ratings in human volunteers. *Appetite.* 1997; 29(1):61–76.
34. Herman CP, Mack D. Restrained and unrestrained eating. *J Pers.* 1975; 43(4):647–60.
35. Tomiyama AJ, Mann T, Comer L. Triggers of eating in everyday life. *Appetite.* 2009; 52(1):72–82.
36. Merrill EP, Cardello A V., Kramer FM, Leshner LL, Schutz HG. The development of a perceived satiety index for military rations. *Food Qual Prefer.* 2004; 15(7-8 SPEC.ISS.):859–70.
37. Slavin J, Green H. Dietary fibre and satiety. *Nutr Bull.* 2007; 32(SUPPL.1):32–42.
38. Burns AA, Livingstone MB, Welch RW, Dunne A, Robson PJ, Lindmark L, et al. Short-term effects of yoghurt containing a novel fat emulsion on energy and macronutrient intakes in non-obese subjects. *Int J Obes Relat Metab Disord.* 2000; 24(11):1419–25.
39. Rolls BJ, Roe LS, Meengs JS, Wall DE. Increasing the portion size of a sandwich increases energy intake. *J Am Diet Assoc.* 2004; 104(3):367–72.

40. Morris E, Roe L, Rolls B. Portion size of food affects energy intake in normal-weight and overweight men and women. *Am J Clin Nutr.* 2002; 76(6):1207–13.
41. Herman CP, Roth DA, Polivy J. Effects of the presence of others on food intake: A normative interpretation. *Psychol Bull.* 2003; 129(6):873–86.
42. de Castro JM, Brewer EM, Elmore DK, Orozco S. Social facilitation of the spontaneous meal size of humans occurs regardless of time, place, alcohol or snacks. *Appetite.* 1990;15(2):89–101.
43. Blundell J, De Graaf C, Hulshof T, Jebb S, Livingstone B, Lluch A, et al. Appetite control: Methodological aspects of the evaluation of foods. *Obes Rev.* 2010; 11(3):251–70.
44. Jeon S-Y, O’Mahony M, Kim K-O. A comparison of category and line scales under various experimental protocols. *J Sens Stud.* 2004; 19(1):49–66.
45. Cardello AV., Schutz HG, Leshner LL, Merrill E. Development and testing of a labeled magnitude scale of perceived satiety. *Appetite.* 2005; 44(1):1–13.
46. Stevens SS, Galanter EH. Ratio scales and category scales for a dozen perceptual continua. *J Exp Psychol Gen.* 1957; 12454(4):375–90.

## APPENDIX

### *Rating Scales*

“Hello participant HC-00, please indicate on a scale of 1-7 how hungry and full you are where 1= not at all hungry/not at all full and 7=extremely hungry/extremely full.

Also note the weight of your food before eating.

- Hunger before eating:
- Fullness before eating:
- Weight of food (in grams) before eating:”

“Hello participant HC-00, please indicate on a scale of 1-7 how hungry and full you are where 1= not at all hungry/not at all full and 7=extremely hungry/extremely full.

Also note the weight of your food after eating.

- Hunger after eating:
- Fullness after eating:
- Weight of food (in grams) after eating:”