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Association of number of bites and eating speed with energy intake: Wearable technology results under free-living conditions

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ABSTRACT

Personalized weight management strategies are gaining interest. However, knowledge is limited regarding eating habits and association with energy intake, and current technologies limit assessment in free-living situations. We assessed associations between eating behavior and time of day with energy intake using a wearable camera under free-living conditions and explored if obesity modifies the associations. Sixteen participants (50% with obesity) recorded free-living eating behaviors using a wearable fish-eye camera for 14 days. Videos were viewed by trained annotators who confirmed *number of bites*, *eating speed*, and *time of day* for each eating episode. Energy intake was determined by a trained dietitian performing 24-h diet recalls. Greater number of bites, reduced eating speed, and increased BMI significantly predicted higher energy intake among all participants ($P < 0.05$, each). There were no significant interactions between obesity and number of bites, eating speed, or time of day ($p > 0.05$). Greater number of bites and reduced eating speed were significantly associated with higher energy intake in participants without obesity. Results show that under free-living conditions, more bites and slower eating speed predicted higher energy intake when examining consumption of foods with beverages. Obesity did not modify these associations. Findings highlight how eating behaviors can impact energy balance and can inform weight management interventions using wearable technology.

1. Introduction

The prevalence of obesity has steadily increased in the United States, with obesity affecting 42% of adults in 2018 (Hales CM, 2020). The growth is believed to be largely driven by excessive calorie intake and overeating ("Preventing Weight Gain.," 2020). Thus, weight management strategies often focus on restriction of calories and food intake (Williams et al., 2019), while also applying behavioral strategies to prevent overeating (Raynor & Champagne, 2016). There is increasing interest in identifying effective strategies related to the duration (e.g., eating speed, number of bites) and timing (i.e., time of day) of eating episodes to prevent excessive energy intake in the treatment of adults who are overweight or with obesity (Ferriday et al., 2015; Raynor & Champagne, 2016; Sonoda et al., 2018). Despite the absence of definitive evidence to support the manipulation of eating duration and timing to decrease energy intake (Raynor & Champagne, 2016), strategies targeting eating behaviors and timing are often advised for weight management (Kinsey & Ormsbee, 2015). The mixed evidence has rendered conclusions unclear regarding the relationship between eating behaviors and energy intake.

Preliminary trials investigating the effect of duration of eating on energy intake among adults show a positive association between eating speed and/or number of bites with energy intake (Andrade, Greene, & Melanson, 2008; Hurst & Fukuda, 2018; Scisco, Muth, Dong, & Hoover, 2011; Shah et al., 2014), while faster self-reported eating speed has been linked with higher body mass index (BMI) in observational studies (Leong, Gray, & Horwath, 2016; Leong, Madden, Gray, Waters, & Horwath, 2011; Otsuka et al., 2006; Sasaki, Katagiri, Tsuji, Shimoda, & Amano, 2003; Tanihara et al., 2011; van den Boer et al., 2017). Some studies also support the use of timing to curb energy intake. Notably, nighttime eating habits are associated with higher energy intake, higher BMI, and/or obesity (Baron, Reid, Kern, & Zee, 2011; Berg et al., 2009; Reid, Baron, & Zee, 2014; Wang et al., 2014; Yoshida, Eguchi, Nagaoka, Ito, & Ogino, 2018), and eating later in the day has been associated with

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slower weight loss than having earlier meals (Garaulet et al., 2013; Jakubowicz, Barnea, Wainstein, & Froy, 2013; Kahleova, Lloren, Mashchak, Hill, & Fraser, 2017). However, there is some ambiguity about the efficacy of intervening on eating duration and timing. A few trials have shown either negative or no associations between eating speed and energy intake (Andrade, Kresge, Teixeira, Baptista, & Melanson, 2012; Spiegel, Kaplan, Tomassini, & Stellar, 1993; Yeomans, Gray, Mitchell, & True, 1997), and one randomized controlled trial reports that consuming most of one's energy intake earlier in the day resulted in greater weight loss (Jakubowicz et al., 2013). The heterogeneity in the literature and limited generalizability might be attributed to the paucity of randomized controlled trials designed to test these hypotheses (Raynor & Champagne, 2016), as well as the small number of eating observations, use of self-reports of eating behaviors, and/or cultural differences in the food supply as many of these studies were conducted in Asian countries (Andrade et al., 2012; Baron et al., 2011; Berg et al., 2009; Garaulet et al., 2013; Jakubowicz et al., 2013; Kahleova et al., 2017; Leong et al., 2016; Leong et al., 2011; Otsuka et al., 2006; Reid et al., 2014; Sasaki et al., 2003; Spiegel et al., 1993; Tanihara et al., 2011; van den Boer et al., 2017; Wang et al., 2014; Yeomans et al., 1997; Yoshida et al., 2018). Further, there has been limited focus on differences in associations between eating speed and energy intake between individuals with and without obesity, despite evidence that weight status may influence the effect of eating speed on energy intake (Shah et al., 2014). Recent evidence suggests that eating slowly reduces energy intake during a controlled meal within the normal weight group (Shah et al., 2014), although it is uncertain whether these 2-day observations in a laboratory are generalizable to free-living conditions. A greater understanding of the modifying effect of BMI on eating behaviors and energy intake is necessary, especially with the use of objective assessments in free-living conditions.

Technological advances are being made to objectively measure caloric intake to detect eating behaviors that correlate with energy intake (Alshurafa et al., 2019). Two studies used a wrist-worn device to count bites through hand-to-mouth gestures in free-living conditions have shown modest correlation between number of bites and caloric intake (Dong, Hoover, Scisco, & Muth, 2012; Scisco, Muth, & Hoover, 2014). However, these experiments rely on participants to turn on/off the camera and do not allow for visually confirming the eating gestures detected by the device. Given that hand-to-mouth gestures during eating episodes do not always represent an eating gesture (Zhang, Alharbi, Nicholson, & Alshurafa, 2017), the validity of number of bites is important to confirm visually. To visually confirm usual eating behaviors, we employ a wearable fish-eye camera that enables us to investigate the association of eating speed, number of bites, and time of day with caloric intake in people with and without obesity. We hypothesize that faster eating speed and eating later in the day are associated with higher energy intake in participants, irrespective of weight status.

2. Methods

2.1. Study sample

Participants were recruited using ResearchMatch, an online tool that matches people who want to participate in studies with researchers seeking volunteers, and study flyers distributed in local cafes and restaurants. Eligibility requirements included adults 18–65 years old with BMI $\geq$18.5 kg/m^2. Participants were excluded from recruitment in the observational study if they were unable to wear study devices (e.g., skin irritation) or did not own a laptop. After the observational study was conducted, we remove one participant without a single meal recorded from the analysis of this paper. Height and weight were obtained using a built-in stadiometer and scale (Health-*O*-Meter Patient Weighing Scale Model 349KLX, McCook, NE, USA). Participants were stratified into two groups: with obesity (BMI $\geq$30 kg/m^2) and without obesity (BMI $<$30 kg/m^2). Stratification was intended to provide a better understanding of whether having obesity imparts unique predictors of eating habits and time of eating on energy intake. The study was performed in accordance with the Declaration of Helsinki and was reviewed and approved by the Northwestern University Institutional Review Board Office, designated by number as STU00204564. All participants provided electronically administered informed consent, collected using REDCap electronic data capture tools hosted at Northwestern University.

2.2. Measures

2.2.1. Wearable camera for visual confirmation

Eating behaviors (i.e., number of bites, eating speed, and eating time of day) were observed using a modified wearable video camera and ancillary equipment developed by our research group. The wearable camera has been previously validated to enable visual confirmation of foods consumed (Alharbi et al., 2018). Participants were asked to wear the wearable camera during waking hours for 2 weeks in a free-living condition. The wearable camera was specifically designed with an augmented fish-eye lens to enable a wider field of view to visually confirm participants' eating behaviors (Fig. 1). Based on prior formative research (Alharbi, 2018) showing the importance of obscuring the camera for privacy concerns, we designed a 3D camera case and ID card cover to conceal the camera to enhance participant willingness to wear the device. The camera and 3D case were worn over participants' clothes, and the card cover could be worn as desired over the case. Orientation and distance from the mouth affect field of view (Alharbi et al., 2018). Participants wore a shoulder strap that secured the device on their bodies to avoid any shifts to the field of view. The camera was positioned around the shoulder with the lens facing the dominant side of the participant's torso to capture the mouth, jaw, neck, utensils, and food while maintaining bystander privacy (Fig. 1). Participants were provided with access to ELAN (Max Planck Institute for Psycholinguistics), a professional video editing software that allowed them to delete video clips they did not want to share with investigators. At the baseline visit, each participant was trained on how to wear the video camera, offload the data onto their laptop at the end of the day, and use the ELAN delete tool to annotate the start and end of eating or drinking episodes (as defined by eating and/or drinking during a discrete period of time). Participants were instructed to eat and drink as naturally as possible and were provided with written, standardized responses to answer questions about using the device, which has been shown to be an effective way to address concerns when approached by bystanders (Kelly et al., 2013; Nebeker et al., 2016). At study completion, a trained annotator reviewed

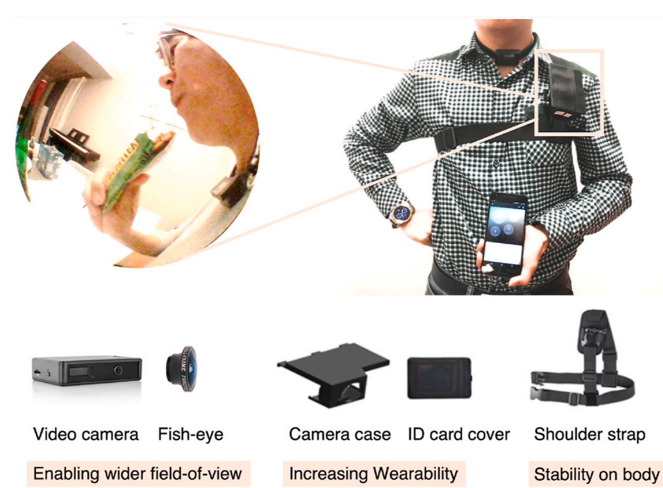

Fig. 1. Participant wearing the camera and video footage collected from the shoulder camera of a person consuming a granola bar. The video camera fish-eye lens enables a wider field of view. The camera case and ID card cover increase wearability, and the shoulder strap improves stability on the body.

all video footage to confirm eating and drinking and labeled each bite during every meal or snack. A bite or eating gesture was defined as a single movement involving any food or beverage being placed into the mouth. Prolonged drinking episodes with sporadic drinking gestures (7 episodes) were not included in the analysis due to the inability to validate the beverage item and/or the duration of consumption. A second annotator verified the labels and corrected any errors performed in labeling. Any conflicts were resolved by a third annotator. Annotators reviewed the video recordings to determine whether the act of eating or drinking that coincided at the time of the diet recall could be visually identified during the eating episode. We included videos in which the bites were clearly visible to ensure accurate labels of bites that were used in our statistical model. In the event that the act of eating or drinking is confirmed within 1 h of the recall, we use the time of the camera (given its greater precision) and include the meal or snack in the analysis.

2.2.2. Energy intake

Energy intake data were collected by a registered dietitian conducting 24-hr dietary recalls, a validated tool used to collect information about dietary intake (Blanton, Moshfegh, Baer, & Kretsch, 2006). Registered dietitians called participants daily to complete the 24-hr dietary recalls. If a participant could not be reached, the recall was completed the next day or at least within 2 days. The dietitian conducted the recalls by telephone and used a 3-stage multiple pass interviewing technique. In the first pass, the participant provided a complete list of all foods and beverages consumed the previous 24 h prior to the call (quick list). During the second pass, the dietitian inquired about descriptions from the quick list (i.e., brand, cooking methods, portion size). The last pass involved a review of the items to ensure items and descriptions were recorded accurately. Food and nutrient data were determined using the Nutrition Data System for Research software versions 2016 and 2017, developed by the Nutrition Coordinating Center (NCC), University of Minnesota, Minneapolis, MN. Given the mixed evidence about the impact of beverage consumption habits on total energy intake, we built both a food- and drink-based model, and a food-based only model. In the food- and drink-based model, energy intake was calculated using both food and drink. In the food-based only model, calories from beverages were excluded from analysis. To provide additional diet detail of the participants, a research dietitian categorized each food item into nine major Nutrition Data System for Research food categories. A mixed dish category was also created to include dishes that had different types of food categories.

2.2.3. Eating behaviors

Number of bites was tallied by counting the number of bites/gestures from food and drink in each episode for each meal and snack that had a 24-h dietary recall and had an existing video recording from the participant. When estimating number of bites for the food-based only model we excluded gestures from drinks. *Meal duration* was defined as the difference in time (in minutes) between the first and last bite during an eating episode and was determined by trained annotators. *Eating speed* was calculated by dividing the meal duration of each eating episode by the number of bites. *Time of day* of the start of the eating episode was identified using the video time stamps.

2.3. Statistical approach

Statistical analyses were performed using R version 3.6.3, and the significance level was set at $P < 0.05$ for all tests. Chi-square (for categorical variables) and independent t-tests (for continuous variables) were performed to compare differences in demographic, clinical, and eating characteristics between participants with and without obesity. To adjust for skewed data, continuous variables were log-transformed when comparing these characteristics between the two groups. The hypotheses and analytical plan were prespecified before data collection. A linear mixed effects model was used to explore the association between energy intake and other factors. Specifically, using data from food- and drink-based gestures, linear mixed-effect modeling was used with repeated measures of energy intake as the outcome, and number of bites, eating speed, time of day, and BMI were used as covariates. A random intercept was included to address the inherent correlation of multiple measured energy intake from the same participant. In addition, to investigate whether BMI modified the associations between eating behaviors and energy intake, we performed additional analysis by including interaction terms of eating behaviors with an obesity variable (0 = without obesity, 1 = with obesity) to the model. We further restricted our analysis to food-related gestures found within the recorded eating episodes due to mixed evidence about the impact of beverage consumption habits on total energy intake (Appelhans et al., 2013; Mattes, Shikany, Kaiser, & Allison, 2011).

For the linear mixed-effect model employed, information for most of the critical parameters were not available during the design stage, and therefore we did not perform power calculation at that stage. However, we conducted a post hoc sample size calculation once we received reliable estimations of these parameters. To be conservative, among the 4 covariates investigated (number of bites, eating speed, time of day, BMI), we always used the lower effect size. With these estimates, a total of 16 participants, obtained as 8 in each group, were each measured at 9 time points. Calculation by PASS 2021 suggests that this sample size would achieve 83% power to detect a difference between the (fixed) group means of at least 1.90. The standard deviation was 1.50. The correlation between measurements within participants was 0.30. A test based on a mixed-model analysis was estimated at a significance level of 0.050. Therefore, we expect that our sample size was sufficiently powered.

3. Results

3.1. Participant characteristics

A total of 32 participants were recruited, 21 enrolled, and 16 (n = 8 with obesity, n = 8 without obesity) completed the study. Of the 5 participants who discontinued the study, two discontinued prior to the start of data collection, and three did not have eating episodes collected by both the camera and the dietitian. Participant characteristics, eating behaviors, and dietary intake are presented in Table 1. Mean (SD) age was 31.9 (11.2) years, and a higher proportion identified as female (62.5%). A total of 653 unique meals collected from 24-h dietary recalls were collected over the 2-week study period, and 211 (32%) corresponding eating episodes were recorded with a wearable video camera. The final analytical sample comprised 155 (24%) eating episodes. Fifty-two eating episodes were excluded because the video data could not be synchronized to micro-behaviors, which impacted label collection, a well-known concern in mobile health research (Zhang et al., 2020). Three were excluded due to improper lighting in the video footage, which impeded accurate footage review, and one eating episode was excluded owing to camera failure in capturing the footage. When examining the dietary intake of the overall sample, the top three food groups consumed were grains (22%), mixed dishes (18%), and meat, fish, poultry, eggs, nuts, seeds and meat alternatives (14%). Among all participants, there was an even distribution of eating episodes throughout the day, with peaks around 8 A.M., 11 A.M.–12 P.M., and 5–6 PM (Fig. 2). Participants with obesity recorded a total of 41 meals, while those without obesity recorded 114 meals. Compared with participants with obesity, those without obesity had a significantly higher mean [SD] number of bites (35.6 [21.7] vs 48.9 [30.7] bites, respectively; $P = 0.004$) and faster eating speed group (3.1 [1.3] vs 4.0 [2.2] bites/min; $P = 0.003$).

3.2. Association between eating behavior or time of day and energy intake

Higher energy intake was associated with greater number of bites (β

Table 1
Demographics, clinical characteristics, and eating behaviors of participants with and without obesity.

Characteristics	Overall (N = 16)	With Obesity (n = 8)	Without Obesity (n = 8)
Age, mean (SD)	31.9 (11.2)	36.4 (12.2)	27.5 (8.6)
Height, mean (SD), cm	168.4 (7.8)	168.6 (9.4)	168.3 (6.4)
Weight, mean (SD), kg	86.4 (25.4)	105.9 (18.2)	66.9 (13.6) 5***
Female n (%)	10 (62.5)	5 (62.5)	5 (62.5)
Race, n (%)			
White	9 (56.3)	4 (50)	5 (62.5)
Black	5 (31.3)	4 (50)	1 (12.5)
Asian	2 (12.5)	0 (0)	2 (25.0)
BMI, mean (SD), kg/m^2	30.4 (8.9)	37.4 (7.0)	23.4 (3.4) ***
Number of bites, mean (SD)	45.4 (29.1)	35.6 (21.7)	48.9 (30.7) *
Eating speed, mean (SD), bites/min	3.7 (2.0)	3.1 (1.3)	4.0 (2.2) *
Energy intake, mean (SD), kcal per meal	564.3 (389.6)	689.0 (407.4)	519.5 (374.7) *
Food groups, (n%)***			
Fruits	16 (4.5)	3 (2.5)	13 (5.5)
Vegetables	39 (10.9)	14 (11.5)	25 (10.6)
Meat, fish, poultry, eggs, nuts, seeds, and meat alternatives	51 (14.2)	17 (13.9)	34 (14.4)
Grains	79 (22.1)	19 (15.6)	60 (25.4)
Dairy	32 (8.9)	11 (9.0)	21 (8.9)
Fats	1 (0.3)	0 (0.0)	1 (0.4)
Sweets	3 (0.8)	0 (0.0)	3 (1.3)
Beverages	49 (13.7)	24 (19.7)	25 (10.6)
Miscellaneous	22 (6.1)	16 (13.1)	6 (2.5)
Mixed Dishes	66 (18.4)	18 (14.8)	48 (20.3)

BMI, body mass index; SE, standard error.
Eating episodes are weighted the same.
Raw values are presented in this table. To compare characteristics between participants with and without obesity, Chi-square (categorical variables) and independent t-tests (continuous variables) were used to compare characteristics of participants with and without obesity. Continuous variables were log transformed prior to conducting independent t-tests.
*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$ between those with and without obesity.

[SE], 4.70 [0.97]; $P < 0.0001$), reduced eating speed (β [SE], −38.35 [13.81]; $P = 0.006$), and higher BMI (β [SE], 13.22 [4.45]; $P = 0.01$). Time of day did not significantly predict energy intake (β [SE], 9.56 [6.14]; $P = 0.12$). There were no significant interactions between obesity, eating behaviors, or time of day with energy intake (Table 2); however, greater number of bites (β [SE], 5.11 [1.07]; $P < 0.001$) and reduced eating speed (β [SE], −38.01 [14.95]; $P = 0.012$) remained significantly associated with energy intake in participants without obesity.

Similar patterns emerged when analyzing only food-based eating gestures (Table 3). Higher energy intake was associated with greater number of bites (β [SE], 4.41 [1.08]; $P = 0.0001$) and higher BMI (β [SE], 13.72 [4.89]; $P = 0.01$), although eating speed was no longer significantly associated with energy intake (β [SE], −24.80 [13.94]; $P = 0.08$). Obesity did not modify the association between eating behaviors and time of day with energy intake (interaction, $P > 0.05$). In the group without obesity, greater number of bites was associated with higher energy intake (β [SE], 5.20 [1.19]; $P < 0.0001$) but was not associated in the group with obesity (β [SE], 0.26 [2.75]; $P = 0.93$).

Given the unexpected outcome that reduced eating speed was associated with increased calorie intake, we explored potential explanations for this result using data from the 10 fastest (mean [SE] speed, 8.79 [0.47] bites/min) and 10 slowest eating episodes (mean [SE] speed, 0.77 bites/min). Mean (SE) BMI was lower among those that had faster versus slower eating episodes (23.50 [0.99] vs 27.98 [2.42] kg/m^2, respectively). Additionally, mean [SE] energy intake was lower in faster eating episodes (379.60 [59.56] kcal) than slower ones (632.80 [110.53] kcal), while eating duration was significantly shorter among the fastest eating episodes (46 [3.92] min) than the slowest (40.55 [34.31] min). A higher percentage of meals within the slowest eating episodes (80%) were

Table 2
Food- and drink-based model: Associations between eating behaviors or time of day and daily energy intake for all eating episodes.

Variables	Main Analysis, β (SE)[a]	Subgroup Analysis[b]		
		Overall Interaction, $\beta_{interaction}$ (SE)	With Obesity, β (SE)	Without Obesity, β (SE)
Intercept	29.76 (160.66)	168.24 (226.49)	550.94 (196.68) **	382.70 (112.31)***
Number of bites	4.70 (0.97) ***	−3.20 (2.81)	1.90 (2.60)	5.11 (1.07) ***
Eating speed, bites/min	−38.35 (13.81)**	−18.57 (43.57)	−56.58 (40.93)	−38.01 (14.95)*
Time of day	9.56 (6.14)	13.13 (13.63)	19.21 (11.45)	6.08 (7.40)
BMI, kg/m^2	13.22 (4.45) *	N/A	N/A	N/A

BMI, body mass index; N/A, not applicable; SE, standard error.
*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.
[a] Linear mixed-effect model with repeated measures where energy intake was the outcome, with covariates for number of bites, eating speed, time of day and BMI and random intercept to address inherent within subject correlation.
[b] Additionally includes interaction term of eating behaviors with an obesity variable.

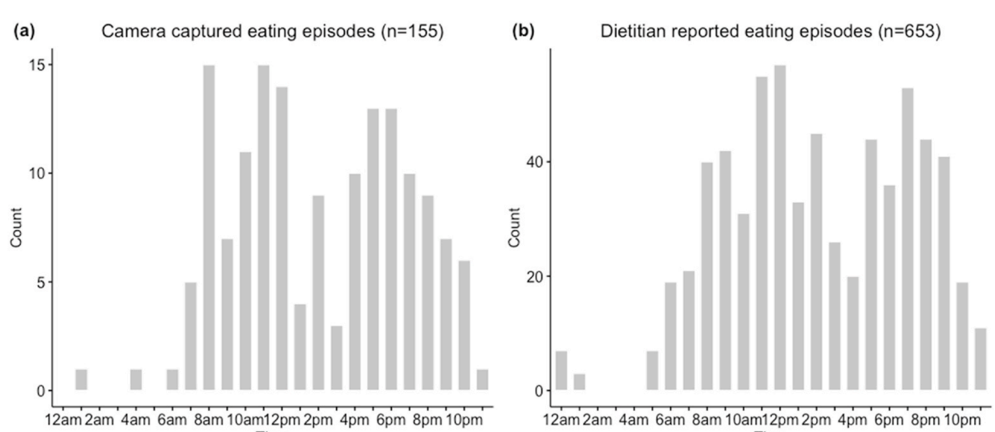

Fig. 2. Frequency distribution of eating episodes throughout the day. (a) Distribution of the number of camera-captured eating episodes (n = 155). (b) Distribution of the number of dietitian-reported eating episodes (n = 653).

Table 3
Food-based only model: Associations between eating behaviors or time of day and daily energy intake with food-based eating gestures[a] only.

Variables	Main Analysis, β (SE)[b]	Subgroup Analysis[c]		
		Overall Interaction, $\beta_{interaction}$ (SE)	With Obesity, β (SE)	Without Obesity, β (SE)
Intercept	−15.34 (173.36)	77.70 (240.19)	470.80 (209.63)*	393.11 (117.26)***
Number of bites	4.41 (1.08) ***	−4.95 (2.99)	0.26 (2.75)	5.20 (1.19) ***
Eating speed, bites/min	−24.80 (13.94)	17.43 (48.12)	−11.33 (45.79)	−28.76 (14.80)
Time of Day	6.23 (6.36)	14.42 (14.14)	16.67 (11.93)	2.25 (7.59)
BMI, kg/m^2	13.72 (4.89) *	N/A	N/A	N/A

BMI, body mass index; N/A, not applicable; SE, standard error.
*$P < 0.05$; ***$P < 0.001$.
[a] Defined as eating episodes where calories from beverages were excluded from analysis.
[b] Linear mixed-effect model with repeated measures where energy intake was the outcome, with covariates for number of bites, eating speed, time of day and BMI and random intercept to address inherent within subject correlation.
[c] Additionally includes interaction term of eating behaviors with an obesity variable.

consumed during screen time (i.e., watching TV, laptop, or phone) compared with the fastest eating episodes (30%).

4. Discussion

Our research aims to understand eating habit and its associations with energy intake to personalize weight management interventions. We therefore examined the associations between eating habits and energy intake among participants with and without obesity. Greater number of bites, reduced eating speed, and higher BMI significantly predicted higher energy intake in the overall sample. When grouping by obesity status, greater number of bites and reduced eating speed remained significantly associated with higher energy intake in the participants without obesity. Similar results were also observed when restricting analysis to food-based eating gestures. Collectively, our findings support the hypothesis that number of bites and eating speed is predictive of energy intake in free-living conditions.

Our finding that reduced eating speed was significantly associated with higher energy intake conflicts with previous studies that used the Bite Counter device to measure eating speed (Dong, Scisco, Wilson, Muth, & Hoover, 2014; Scisco et al., 2011; Scisco et al., 2014). The mixed evidence may be partially explained by differences in capturing eating speed; whereas previous studies measured eating speed in controlled environments without visual confirmation of the eating speed, our study used wearable cameras in free-living conditions. Our findings were plausible given that the slowest eating episodes most likely occurred during screen time, a type of distraction associated with higher energy intake (Mekhmoukh, Chapelot, & Bellisle, 2012; Temple, Giacomelli, Kent, Roemmich, & Epstein, 2007), poorer food choice (Shang et al., 2015; Trofholz, Tate, Loth, Neumark-Sztainer, & Berge, 2019), and obesity (Rogerson et al., 2016). Association between reduced eating speed and higher calorie intake may be attributed to greater distractions during the eating episode and, consequently, a longer eating duration (Barrington & Beresford, 2019). Although the association between reduced eating speed and number of bites with energy intake was not significant among the participants with obesity, the direction of effect estimates remained unchanged from the overall analyses. Future studies should include a larger sample of video recordings of the obesity group to ensure adequate power to detect differences by obesity status.

When analyzing food-based gestures only, eating speed was no longer significant despite the number of bites remaining a significant predictor of energy intake. We observed that, although not statistically significant, the removal of drink-based gestures resulted in smaller effect size between eating behaviors and energy intake compared with analyses using all food- and drink-based gestures, likely due to greater variability in the data (Tables 2 and 3). This study provided formative findings about the impact that food and beverage consumption have on associations between eating behaviors and caloric intake. The distinction between food- and drink-based gestures by wearable technology will also be critical to consider in research using wearable devices, which can help resolve the conflicting evidence about the degree of contribution foods, as well as caloric beverages, have on energy intake (Appelhans et al., 2013; Mattes et al., 2011).

To our knowledge, this is the first study to identify associations between eating behaviors with energy intake in free-living conditions using visual confirmation. Another strength of the study is the integration of technology with self-reported diet assessments, which can increase the validity of diet data by addressing the different biases inherent with each approach (Alshurafa et al., 2019). Our study is limited by the small sample size and, subsequently, the small number of participants in each subgroup. However, owing to the study design that included multiple eating episodes from each participant, we were able to capture 155 distinct, analyzable eating episodes, improving our ability to detect significant associations. Despite the purposive sampling approach based on weight status, participants with obesity had fewer number of recordings than participants without obesity. This could be due to several factors. Participants with obesity may have consumed fewer but more energy dense meals (as shown in the significant difference in calorie intake per meal). Alternatively, participants with obesity may not have been as comfortable recording all their meal intake. Future research should assess whether people with obesity are less likely to record video of food intake. While we encouraged participants to wear the device throughout the day, the camera was not consistently worn; therefore, not all eating episodes could be verified by the 24-h dietary recalls. Participants and/or third-party bystanders may have had privacy concerns or felt self-conscious, thus influencing wear adherence and/or changes in eating behavior. We attempted to address this by informing participants to be themselves, and to not adjust their eating patterns, reminding them that this is not a weight loss study. However, future studies should consider incorporating a smaller video camera while obfuscating the participant's private information that is irrelevant to the studies. Further, greater reassurance to minimize perceived judgment of eating behaviors should be incorporated at the beginning of the study to increase wear adherence. Finally, classification of participants using BMI may have biased our results, as participants with high lean mass or high percent body fat may have been erroneously classified as obese or normal weight, respectively.

In conclusion, in a cohort of 16 participants in free-living conditions, greater number of bites, reduced eating speed, and higher BMI significantly predicted higher energy intake. Results from this study provide groundwork to identify potential targets for weight management interventions. Our analyses support the conclusion that number of bites and eating speed are potential eating behavior targets to prevent excessive energy intake. We also observed that combining food and beverage consumption may affect these associations. Further investigation is needed on types of food and chewing duration, as well the impact of eating behaviors on energy intake in those with and without obesity under free-living conditions. By addressing these questions, the implications of potential eating behavior targets on energy intake and/or weight loss could be further understood to improve the quality of individualized weight loss approaches.

Author contributions

NA contributed to study design; NA, SZ, and HZ collected and/or analyzed the data. NA, HZ, and AWL wrote initial drafts of the manuscript. NA and AWL had primary responsibility for final content. All authors reviewed and commented on subsequent drafts of the manuscript.

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Data statement

Deidentified data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability

Not applicable.

Ethics statement

EthicsStatement is provided in the manuscript and below.

The study was performed in accordance with the Declaration of Helsinki and was reviewed and approved by the Northwestern University Institutional Review Board Office, designated by number as STU00204564. All participants provided electronically administered informed consent, collected using RedCap electronic data capture tools hosted at Northwestern University.

Declaration of competing interest

The authors report no conflicts of interest to disclose.

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