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Objective Determination of Eating Occasion Timing (OREO): Combining Self-Report, Wrist Motion, and Continuous Glucose Monitoring to Detect Eating Occasions in Adults With Pre-Diabetes and Obesity

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Abstract

Background: Accurately identifying eating patterns, specifically the timing, frequency, and distribution of eating occasions (EOs), is important for assessing eating behaviors, especially for preventing and managing obesity and type 2 diabetes (T2D). However, existing methods to study EOs rely on self-report, which may be prone to misreporting and bias and has a high user burden. Therefore, objective methods are needed.

Methods: We aim to compare EO timing using objective and subjective methods. Participants self-reported EO with a smartphone app (self-report [SR]), wore the ActiGraph GT9X on their dominant wrist, and wore a continuous glucose monitor (CGM, Abbott Libre Pro) for 10 days. EOs were detected from wrist motion (WM) using a motion-based classifier and from CGM using a simulation-based system. We described EO timing and explored how timing identified with WM and CGM compares with SR.

Results: Participants ($n = 39$) were 59 ± 11 years old, mostly female (62%) and White (51%) with a body mass index (BMI) of 34.2 ± 4.7 kg/m^2. All had prediabetes or moderately controlled T2D. The median time-of-day first EO (and interquartile range) for SR, WM, and CGM were 08:24 (07:00-09:59), 9:42 (07:46-12:26), and 06:55 (04:23-10:03), respectively. The median last EO for SR, WM, and CGM were 20:20 (16:50-21:42), 20:12 (18:30-21:41), and 21:43 (20:35-22:16), respectively. The overlap between SR and CGM was 55% to 80% of EO detected with tolerance periods of ±30, 60, and 120 minutes. The overlap between SR and WM was 52% to 65% EO detected with tolerance periods of ±30, 60, and 120 minutes.

Conclusion: The continuous glucose monitor and WM detected overlapping but not identical meals and may provide complementary information to self-reported EO.

Keywords

chrononutrition, fasting, intermittent fasting, meal detection, meal timing, wearable sensors

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Introduction

Nearly, 40% of United States adults live with obesity,[1] which is a leading risk factor for type 2 diabetes (T2D).[2] Nearly, 10% of the US population has T2D, and its prevalence is growing.[3] While both conditions require individuals to perform daily self-management activities, patients experience barriers to successful self-management,[4] and thus may not meet goals, such as target glycosylated hemoglobin (HbA1c). Eating patterns, such as the timing of meals, are a key modifiable determinant of obesity and T2D.[5-7] Understanding an individual's eating timing is a crucial part of designing a tailored intervention for treatment and prevention, as nutrition therapy must be individualized.[8]

The frequency of eating occasions (EOs) is positively associated with obesity in adults[9] and meal timing may influence the risk of metabolic disease.[6,9] Identifying the timing, frequency, and distribution of EO is thus important for assessing eating behaviors, especially when designing interventions for managing and preventing obesity and T2D, as much eating behavior is automatic.[10] However, it is difficult to obtain large-scale data on meal times and frequency.

Currently, insight into EO timing comes mainly from self-reported events. Short-term dietary assessment methods, such as dietary recalls and food records, ask individuals to report when EO occur.[11] However, people often significantly misreport dietary intake,[12] often failing to recall or forgetting to log EOs, or inaccurately indicating their timing.[13] Self-reported intake were found to underestimate intake by more than 20% in many comparisons to doubly labeled water.[14] Data omissions may be more likely for people with obesity,[15] suggesting an independent account of eating behavior is needed. Recently, there have been significant advances in the development of objective assessments, from continuous glucose monitors (CGMs) and body-worn sensors.[16] Driven by the need for meal identification in artificial pancreas systems, methods have been developed to identify an EO and estimate its carbohydrate content from CGM readings.[17] While such systems can identify meals automatically, they have been mainly developed for individuals with type 1 diabetes (T1D), where all insulin is exogenous and this information can be included in the algorithm, and have not been widely tested in the T2D setting where endogenous insulin makes the task more challenging. Body-worn sensors use features, such as motion (of the wrist or head),[18] audio (e.g., capturing chewing noises),[19] or a combination of modalities to identify meal times and food type.[20,21] In particular, wrist motion (WM) has been used in free-living studies to detect meal times and energy intake.[22] However, body-worn sensors have been assessed in general populations and have yet to be leveraged for identifying meal timings in individuals with obesity and pre-diabetes. In this work, we aim to describe eating patterns using self-report (SR), CGM, and WM-actigraphy methods for detecting EO timing in adults with obesity and pre-diabetes under free-living conditions.

Methods

Design

The data were collected as part of an ancillary study using a sub-group of participants in The *Personal Diet Study* (NCT: NCT03336411), a behavioral weight loss intervention.[23,24] Data were collected at baseline, prior to randomization and intervention initiation. Eligible participants were between 18 and 80 years old, had a body mass index (BMI) of 27 to 50 kg/m^2, and had pre-diabetes or moderately controlled T2D (defined as an HbA1c $\leq$ 8.0% while managed with lifestyle alone or lifestyle plus metformin), but were otherwise healthy. Additional details regarding exclusion criteria have been reported elsewhere.[23] This study was reviewed and approved for Human Subjects Research by the NYU Grossman School of Medicine Institutional Review Board (#17-00741). All participants signed an informed consent prior to data collection.

Measurements

Eating patterns were assessed over 10 days using three methods. The first method was SR, where participants entered date- and time-stamped EO into the Personalized Nutrition Project (PNP) smartphone app. An EO included any food or drink (aside from water) greater than 0 kcals. Participants were instructed to log EOs in the PNP app in real-time. A member of the study team reviewed logged EOs every 1 to 2 days, and any unusual EOs (e.g., 3:00 am) were verified by asking the participants. Concomitantly, participants were instructed to wear an ActiGraph watch (ActiGraph GT9X-BT; Pensacola, FL, USA) on their dominant hand to measure WM. Due to the limited daily battery life, participants were instructed to remove their ActiGraph and charge while sleeping. Participants were also fitted with a CGM (Abbott Freestyle Libre Pro, Abbott Park, IL, USA) on their arm, which measured glucose throughout the study period. The CGM provides data at 15-minute intervals that represent the average glucose over the prior 15 minutes. The WM and CGM data were used to detect mealtimes as discussed below.

WM Meal Detection Methods

Eating occasions were identified from WM data by applying a two-stage neural network analysis developed in previous studies for the ActiGraph's three-axis accelerometer and gyroscope data.[25,26] Data were recorded at 60 Hz and downsampled to 15 Hz for analysis. In the first stage of analysis, a sliding six-minute window is analyzed to calculate the local probability of eating $P(E_w)$.[25,26] This neural network uses three 1D convolution layers, a pooling layer and a dense layer. The window length and stride are 6 minutes and 15 seconds. All model and window parameters were optimal choices according to the original work. In the second stage of analysis, the all-day sequence of $P(E_w)$ is analyzed to calculate the day-level probability of eating $P(E_d)$.[25,26] This neural

network uses a single bidirectional RNN layer and a dense layer applied to each timestep simultaneously. By analyzing the entire day of data all at once, it can use context related to daily patterns of eating to improve detection performance. The day-level analysis helps reduce false positive detections.[25,26] In detail, first the data is input to a window-based neural network with a window size of six minutes and a stride of 15 seconds. The network outputs a probability of eating $P(E_w)$ ranging from 0 (unlikely any eating occurred during this time window) to 1 (very likely eating occurred). The sequence of $P(E_w)$ is then downsampled to 0.01 Hz (about one sample per minute), which is sufficient for analyzing the daily pattern of eating. A second neural network takes as input a sequence of 850 $P(E_w)$ values (approximately 24 hours, padded with zeros for time in which no WM data are available) to calculate the daily probability of eating $P(E_d)$. These output probabilities are then threshold at a value of 0.04 to identify times of eating throughout the day.

The classifiers were trained on data collected in previous studies,[25,26] which ensured no leakage between training and test data. In the training data, 351 participants recorded WM for one day each and self-reported the start and end times of all meals and snacks (hence called EOs).[26] In total, 4680 hours of data containing 1063 eating episodes were used for training the classifiers.[25] The window-based classifier alone detected 87% of eating episodes with 1.9 false positives per true positive (FP/TP) detection, while the daily pattern classifier improved the detection rate to 89% and reduced FP/TP to 1.5.[25] Thus, the method has good sensitivity but detects numerous false positives, in part because non-eating is highly imbalanced with eating (approximately 20-1.2 total hours per day). Open-source software to run these classifiers on ActiGraph data is publicly available (https://cecas.clemson.edu/ahoover/bite-counter/).

CGM Meal Detection Methods

The second approach to objectively determine mealtimes was simulation-based explanation (SBE),[27] which: (1) uses simulation to forecast blood glucose and finds when simulations diverge from observations (divergent point), (2) generates blood glucose forecasts based on varied meal configurations, and (3) identifies which, if any, meal explains the difference between forecast and actual BG (see Supplemental Figure 1).

To simulate meals, we used Glucose-Insulin Model (GIM), a differential equation-based physiological model of the glucose-insulin system that simulates glucose and insulin dynamics, and the effects of meals.[28] Glucose-Insulin Model uses a forcing function strategy to learn parametric models representing different systems, such as glucose, insulin, and unit processes like glucose rate of appearance.

To begin, we continually update GIM using observed variables (eg, exogenous insulin) every minute and output predicted glucose. To find a divergence time t, we compute the mean difference between the recorded CGM values G and predicted glucose G' over a time window ζ: $|G'[t-\zeta:t]-G[t-\zeta:t]|>\varnothing$. If the difference is greater than our threshold $\varnothing$, that time is considered a divergent point. When a divergent point is found, we look backward in time for a meal that could explain it. We do this by generating predicted glucose values for varying meal configurations: m_{st} (meal start time), m_c (meal size), and m_{du} (meal duration). Glucose-Insulin Model is used to simulate the effects of each of these meals. To find the meals that best explain the divergence, we compute the Euclidean distance between G' and G, $\frac{\sqrt{\sum_{i=m_{st}}^{t}\left|G'(i)-G(i)\right|^2}}{t-m_{st}}$, and select the meal with the smallest distance below a threshold $\in$.

The original SBE was developed for individuals with T1D who use CGM and insulin pump therapy and wore activity monitors.[27] The same method was applied in this study but in individuals with pre-diabetes or moderately controlled T2D, and who did not use activity monitors or exogenous insulin. Since these unmeasured factors can influence glucose, we can no longer expect every deviation to be due to a meal. Thus, the algorithm was modified as follows. First, we calculated the difference between G' and G over a longer time range including past the divergent point ($t^* = \max(t, m_{st}+m_{du})+\Delta$). Second, we stored alternate meals below our threshold to allow backtracking if, as new data are collected, the accepted meal does not match observations. Finally, if the algorithm cannot find a meal that explains the difference between observations and predictions, we automatically move forward in time. See the Supplemental Material for parameters.

Statistical Analysis

Demographic variables were summarized as mean (standard deviation) for continuous variables and count (proportion) for categorical variables. Five EO characterizations were examined: number of EO, first EO, last EO, 95% window eating, and eating midpoint. Specifically, for a participant at one day in one method, (1) the number of EO was defined as sum of all self-reported EO within a 24-hour period. Eating occasions within 15 minutes of each other were combined into a single EO. (2) The first EO was defined as the time of the participant's first meal and (3) the last EO is the time of the participant's last meal. (4) The 95% window eating is defined as the as the 95% interval of all EOs entered in the PNP app, as previously defined.[29,30] (5) The eating midpoint is the median time between the first EO and last EO. Pairwise Spearman's correlation tests were conducted for these five EO characterizations among SR, WM, and CGM, respectively. We also compared the timing of individual EOs identified by SR, WM, and CGM. Self-report meals are identified by start time, while CGM and WM identify start and end time.

Thus, if the start time of an SR EO is within an EO window identified by CGM or WM, we consider that a match. To compare CGM and WM, a match is an EO where the windows overlap. Finally, given that SR timings may be noisy (eg, due to reporting a planned meal, or forgetting and logging mid-meal or post-meal), we also examined how the methods correspond when allowing a tolerance window (eg, allowing a match if the times are within X minutes, for varying X). We tested tolerance windows of: ± 5, 10 15, 30, 60, and 120 minutes.

Results

Characterization of Meal Timing

The flow of participants is presented in Figure 1 and participant characteristics are presented in Table 1. As shown in Table 2, the CGM detected an earlier first EO and later last EO than other methods. The median first EO detected by CGM was approximately 1.5 hour before the first SR EO and approximately 3.0 hour before the median first WM EO. The median first EO detected by WM was within 45 minutes of the median SR first EO. The last EO detected by SR and WM were very similar, while CGM identified a much later last EO. The CGM method detected the longest eating window, while WM detected the shortest. Examining pairwise correlations between mealtimes using Pearson's correlations (Figure 2), we found significant positive correlations between the first EO identified by SR and CGM ($r = 0.534$, $P = .01$), first EO identified by CGM and WM ($r = 0.325$, $P = .004$), and the eating midpoint identified by CGM and WM ($r = 0.253$, $P = .03$). There was also a negative correlation between the eating midpoint identified by SR and WM ($r = -1.0$, $P < .0001$).

Comparison of Meal Detection Methods

Table 3 reports the overlap between CGM and SR, WM, and SR, and CGM and WM for each tolerance period. With tolerance of ± 0, 5, and 10 minutes, less than 40% of EOs were identified by both WM and CGM. The overlap between SR and CGM was between 55% and 80% of EO detected with tolerance periods of ± 30, 60, 120 minutes. The overlap between SR and WM was between 52% and 65% EO detected with ± 30, 60, 120 minutes of tolerance periods. Furthermore, the overlap between WM and CGM was approximately 23% regardless of tolerance used. Finally, we examined the percentage of meals identified by all methods by analyzing matches on days for which all three modes were used. For tolerance levels from ± 0, 10 and 15 minutes, there were no matching meals identified by all methods. At 30 minutes, 4% of SR meals were also found by CGM and WM, while 7% were found for tolerances of both 60 and 120 minutes. Unfortunately, only one participant had an overlap of all three methods over three days.

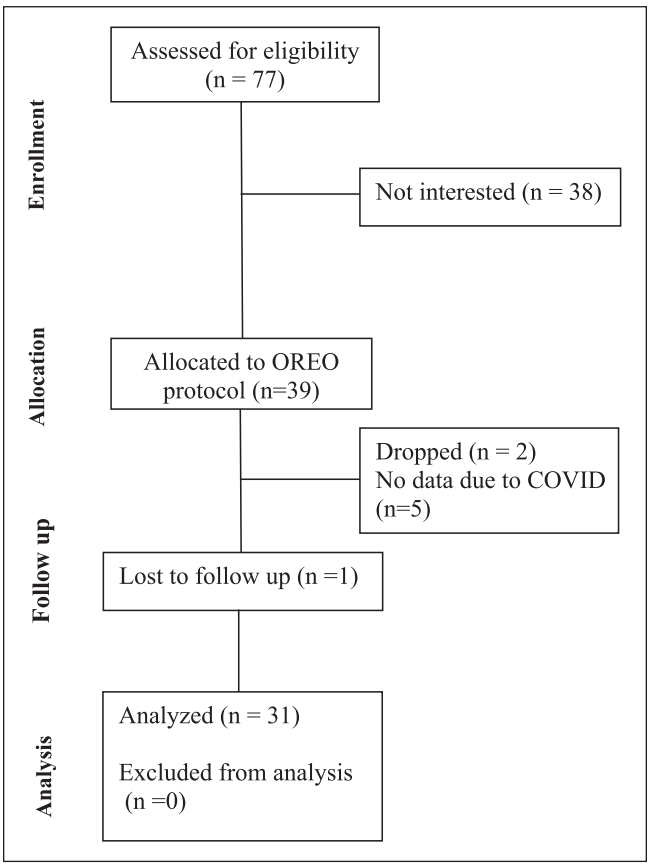

Figure 1. Study flowchart.

Table 1. Baseline Characteristics.

Variable	All ($n = 39$)
Age (years)	52 ± 11
Sex (% Female)	62
Hispanic (% non-Hispanic)	79
Race	
White (%)	51
African American (%)	28
Other (%)	21
Height (cm)	166.0 ± 9.6
Weight (kg)	94.0 ± 14.1
BMI (kg/m^2)	34.2 ± 4.7
HbA1c (%)	5.9 ± 0.6

Data are reported as mean ± SD; race: "Other" includes Asian, Native Hawaiian, or Other Pacific Islander, American Indian, Alaska Native Asian, or unknown.
Abbreviations: BMI, body mass index; HbA1c, glycosylated hemoglobin.

Discussion

The purpose of this study was to compare subjective and objective assessment of EOs in free-living conditions using three methods for detecting meals. Ultimately, we aim to minimize

Table 2. Eating Patterns Measured by SR, WM, and CGM.

Variable	SR	WM	CGM
EO (#/day)	3 (2-4)	4 (3-6)	7 (5-10)
First EO, (hh: mm)	08:24 (07:00-09:59)	9:42 (07:46-12:26)	06:55 (04:23-10:03)
Last EO, (hh: mm)	20:20 (16:50-21:42)	20:12 (18:30-21:41)	21:43 (20:35-22:16)
95% eating window, (h, min)	10:34 (6:49-12:35)	9:08 (6:42-12:41)	13:10 (9:23-15:55)
Eating midpoint, (hh: mm)	13:34 (11:48-15:39)	15:32 (12:53-17:33)	14:06 (11:54-16:19)

Data are reported as median and (interquartile range) for meal start times.
Abbreviations: SR, self-report; WM, wrist motion; CGM, continuous glucose monitor; EO, eating occasion.

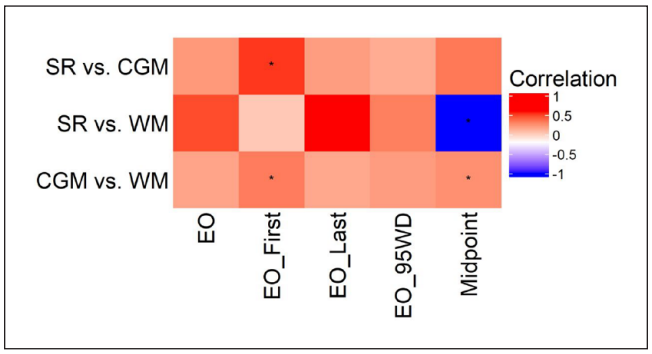

Figure 2. Pairwise correlation between SR, CGM and WM.
Abbreviations: SR, self-report; CGM, continuous glucose monitor; WM, wrist motion; EO, eating occasion; EO_First, first eating occasion of the day; EO_Last, last eating occasion of the day; EO_95WD, eating window; Midpoint, eating midpoint.
*$P < .05$.

Table 3. Percentage Overlap Between SR, CGM, and WM for Varying Tolerance Levels (in Minutes).

Tolerance	SR vs. CGM	SR vs. WM	CGM vs. WM
0	28.4	17.4	22.6
+5	33.8	30.4	22.6
+10	36.5	30.4	22.6
+15	41.9	39.1	22.6
+30	55.4	52.2	22.6
+60	64.9	65.2	22.6
+120	79.7	73.9	22.6
−30, +120	64.9	65.2	22.6

Abbreviations: SR, self-report; WM, wrist motion; CGM, continuous glucose monitor.

the errors associated with self-reported dietary intake data by adding objective measures. Accurate determination of EO is critical for better understanding the relationship between eating patterns and co-morbid conditions (e.g., obesity, T2D) and to ultimately deliver behavioral lifestyle interventions (e.g., time-restricted eating). For example, when a meal is detected, this can be used to improve insulin therapy (e.g., reminders for missed insulin), or deliver behavioral information. For behavioral treatment, automated meal detection could trigger intervention prompts (such as reminders to eat more slowly or limit portion size), or queries about factors that might affect behavior (such as patient mood, environment, and current access to different foods). At a population level, reliance on SR significantly limits the duration of data that can be collected due to participant burden. Instead, using automated and objective methods will enable us to move beyond descriptive analysis of meals and their timing to potentially understand the causal relationships between eating behavior and disease risk. Meal detection can provide individuals with more insight into their eating behavior, thus providing opportunities for personalized feedback on eating frequency and timing of EO.[31]

In the current study, we found meal detection from body-worn sensors is feasible beyond T1D and CGM. A continuous glucose monitor and WM may provide complementary eating pattern information to self-reported methods. Notably, this is to our knowledge, the first use of CGM to detect meals in individuals with pre-diabetes and moderately controlled T2D and using a CGM providing 15-minute averages (rather than actual values every 5 minutes). Despite this significantly more challenging scenario, with less frequent data, the potential of confounding due to endogenous insulin, and a lack of data on physical activity, we found that the CGM can identify meals that are also identified with WM and corresponds strongly to SR. Furthermore, we found that both objective methods, WM and CGM, detect more EOs than SR, suggesting that they may be able to identify omissions. WM alone detected the shortest eating window, while CGM identified the longest and therefore much earlier and later EOs. These latter findings suggest that there may be time-based omissions in SR (e.g., late night snacking). However, we did not include data on sleep and physical activity, which may provide further insight into SR omissions.

Our analyses of each method using tolerance periods (0-120 minutes) shows interesting findings, such that at a tolerance level of 0 minutes, there was overlap of $< 40\%$ when comparing the three methods. Given that SR relies on participants actively logging their meals, it is likely that the two objective methods identify different meals that were either not logged or logged at a different time than the

actual EO. As the tolerance level is increased, these meals are then matched to those identified automatically. For example, at the 30-minute tolerance period, there was overlap of 55% between SR and CGM of EOs detected and 52% overlap between SR and WM of EOs detected. Even with extreme tolerance periods (i.e., 2 hours ± an EO detected), there was not 100% overlap of EOs. Wrist motion and CGM overlap were the same regardless of the tolerance period, indicating that the objective methods are complementary and identifying distinct sets of meals rather than disagreeing about their timing.

The key limitation of this work is the absence of ground truth. While the data were collected in free-living conditions, which make it a realistic representation of real-world use, it means we do not have direct observation of EOs. We focused on correspondence between methods rather than benchmarking CGM and WM against SR, as errors are known to exist in SR based on how EOs are defined by the participants or by researchers.[32] In addition, there may have been incomplete days due to non-adherence to the objective measures (e.g., forgetting to wear the ActiGraph after charging). In this case, failure to capture an EO may not have been the fault of the device (SR or WM) but, rather, non-adherence on the part of the participant. Furthermore, despite our best efforts, we did not have data that included overlap of all three measures. Future work is needed to understand how all three methods correspond to actual EO timing.

Conclusions

We present a comparison of objective and subjective assessments of EO timing in adults with pre-diabetes and obesity. Detecting EO may be improved with objective measures, such as WM and CGM. We found that while CGM has not previously been used in this population, it can be used to identify meals. WM provides real-time indication of EO timing and identifies meals that may be missed by CGM. Depending on tolerance level, CGM overlaps SR on 55% to 80% of EOs, while WM overlaps SR on 52% to 65% of EOs. In future work, we aim to examine how CGM and WM can be used to provide complementary and more robust identification of meal timing.

Abbreviations

BMI, body mass index; EO, eating occasion; CGM, continuous glucose monitor; WM, wrist motion; SR, self-reported; T2D, type 2 diabetes; PNP, personalized Nutrition Project; SBE, simulation-based explanation.

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Declaration of Conflicting Interests

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: C.J.P. is the CEO of TAIN Nutrition, LLC. No other authors have conflicts of interest to disclose.

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Supplemental Material

Supplemental material for this article is available online.

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