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Chrononutrition Patterns in People Who Attempted Weight Loss in the Past Year: A Descriptive Analysis of the National Health and Nutrition Examination Survey (NHANES) 2017–2020 Pre-Pandemic

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Abstract: Introduction: Obesity is associated with cardiometabolic diseases, and chrononutrition has become a novel weight loss strategy. However, few have characterized chrononutrition patterns among people attempting weight loss. This study characterizes chrononutrition patterns in a nationally representative sample of U.S. adults who attempted weight loss in the past year through dietary modifications by weight change and adiposity. Methods: This cross-sectional analysis utilizes NHANES 2017–2020 data. Chrononutrition patterns were assessed using 24 h dietary recalls. Participants self-reported weight loss attempts in the past year and if they tried using diet modification. Weight change (loss, maintenance, and gain) was defined based on differences in current weight and weight one year prior. We used latent profile analysis and descriptive statistics. Results: The sample included 2107 participants who attempted weight loss in the past year through diet modification (median age 47; 58% women and 62% white). Individuals who gained weight (vs. loss) had longer hours between waketime and the first eating (1.78 vs. 1.62 h, $p = 0.024$), consumed a lower proportion of calories later in the day (43% vs. 52%, $p < 0.001$), and ate less frequently (5.20 vs. 5.43 episodes, $p = 0.008$). Participants with obesity had the shortest eating window (11.77 vs. 12.22 h, $p = 0.02$) despite a longer delay between waketime and the first eating (1.80 vs. 1.29 h, $p < 0.001$) and lower eating frequency (5.16 vs. 5.97, $p < 0.001$). Conclusions: Variations in eating timing, eating episodes, and caloric distribution suggest that chrononutrition may play a role in personalized weight management strategies.

Keywords: chrononutrition; weight loss; obesity; adult

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Academic Editor: Iain A. Brownlee

Received: 28 February 2025
Revised: 8 April 2025
Accepted: 23 May 2025
Published: 3 June 2025

Citation: Kim, N.; Jang, H.; Hawkins, M. Chrononutrition Patterns in People Who Attempted Weight Loss in the Past Year: A Descriptive Analysis of the National Health and Nutrition Examination Survey (NHANES) 2017–2020 Pre-Pandemic. *Dietetics* **2025**, *4*, 24. https://doi.org/10.3390/dietetics4020024

1. Introduction

Obesity is a well-established risk factor for multiple cardiometabolic diseases and has been rising at an alarming rate in the United States over the past few decades. According to the most recent national estimates, 40.3% of U.S. adults have obesity [1,2], a significant increase from previous decades. In response to these risks, clinical guidelines and public health initiatives emphasize weight management through lifestyle interventions, primarily focusing on dietary modifications and physical activity [3,4]. Common dietary recommendations include caloric restriction, macronutrient adjustments, and portion control, while physical activity guidelines promote increased aerobic exercise and resistance training to enhance metabolic health. Both strategies have been shown to result in 5–10% weight loss and significant improvements in insulin sensitivity, blood pressure, and lipid profiles [5,6]. However, while what and how much individuals eat have been the cornerstone of weight loss strategies, when people eat—a concept known as Chrononutrition—has received comparatively less attention despite emerging evidence linking it to weight regulation and metabolic health [7–9].

Chrononutrition refers to the alignment of eating timing and frequency with the body's circadian rhythms, which regulate numerous physiological processes, including metabolism, hormone secretion, and energy balance [9–11]. The central circadian clock, located in the suprachiasmatic nucleus of the hypothalamus, synchronizes peripheral clocks in metabolic tissues such as the liver, adipose tissue, and pancreas [12–16]. The central and peripheral circadian clocks regulate key metabolic processes, such as insulin secretion, glucose metabolism, lipid oxidation, appetite signaling, and energy balance, all of which align with the body's daily rhythms to support metabolic health and influence weight gain and loss. Importantly, eating timing acts as a zeitgeber for peripheral clocks, meaning that food intake at inappropriate times (e.g., late at night) can disrupt metabolic homeostasis, increasing obesity risk. For example, studies suggest that eating earlier in the day, maintaining consistent eating timing, and limiting late-night energy intake are associated with greater metabolic efficiency and improved weight management outcomes, while late-night eating has been associated with impaired glucose tolerance, reduced fat oxidation and mobilization, and increased body mass index (BMI) [11,17–21]. However, despite increasing evidence supporting the role of food timing in weight management, prior studies have characterized the use of traditional weight loss strategies (e.g., caloric restriction, increased water intake) in general adult populations [4], while eating timing patterns remain underexamined. Furthermore, little is known about whether specific chrononutrition patterns are associated with weight loss success or obesity status. A deeper understanding of these variations can provide critical insights into optimizing dietary modifications for more effective weight management strategies.

To address this knowledge gap, the present study aimed to characterize chrononutrition patterns in US adults who attempted weight loss within the past year using a nationally representative sample of pre-pandemic National Health and Nutrition Examination Survey (NHANES) 2017–2020 data. We sought to identify key differences in eating timing, eating frequency, caloric distribution across eating occasions and eating windows among those who attempted weight loss through dietary modification. Additionally, we stratified findings by subgroups based on weight change percentage, BMI, and waist circumference to capture variations in dietary patterns and eating timing strategies across individuals with differing cardiometabolic profiles. This research seeks to enhance our understanding of how eating timing behaviors align with weight loss attempts, informing future public health interventions for obesity prevention and management.

2. Materials and Methods

2.1. Study Design

This cross-sectional study utilized the most recent available NHANES data from two survey cycles: the complete 2017–2018 cycle and partial data from the 2019–2020 cycle (data collected through March 2020), prior to data collection being disrupted by the COVID-19 pandemic. NHANES was selected for this study because its rigorous multistage probability sampling approach ensures a nationally representative sample of the U.S. population, including individuals aged 60 and older, African American and Hispanic populations, and individuals with low incomes. This strategy enhances the generalizability of the study findings [22]. Data collection consists of in-home health interviews and physical examinations conducted at a Mobile Examination Center (MEC) [23]. The study protocols were approved by the National Center for Health Statistics Ethics Review Board (Protocol #2018-01), and all participants provided written informed consent prior to data collection. For this analysis, we included participants aged 18 or older. Exclusion criteria included pregnancy and missing data on weight loss attempt status and diet. We included 5287 participants, of whom 2187 reported a weight loss attempt and 2107 reported a diet modification.

2.2. Diet Assessment

Dietary intake was assessed using one or two 24 h dietary recalls. The first was conducted in person at the MEC, while the second was completed via a telephone follow-up (PFU) 3 to 10 days after the first recall [24]. One recall was conducted on a weekday and the other on a weekend to capture variations in dietary intake. An eating episode was defined as the consumption of any calorie-containing meal, snack, or beverage. This analysis averaged dietary data from both recall days to estimate the usual intake. NHANES follows a standard 24 h recall protocol based on the midnight-to-midnight period. Accordingly, the first eating episode was identified as the initial caloric intake after 12:00 a.m., and the last eating episode was determined as the final caloric intake before the following midnight. The eating window was calculated as the duration between the first and last intake. Sleep-related variables (e.g., hours between first eating and waketime and hours between last eating and bedtime) were calculated based on self-reported bedtime and waketime. Eating occasion skipping was defined as the absence of a self-defined eating occasion (e.g., breakfast, lunch, dinner, or snack) based on how participants labeled each eating episode during the 24 h dietary recalls. Additionally, we evaluated the participants' overall diet quality using the Healthy Eating Index 2015 (HEI-2015), which ranges from 0 to 100, with higher scores reflecting better overall diet quality [25].

2.3. Weight Loss Attempt

Weight loss attempts were assessed using a questionnaire that asked, "During the past 12 months, have you tried to lose weight?" Participants were classified into two groups based on their responses: yes or no. Weight change was defined as the difference between measured current weight and self-reported weight a year ago. Weight change status was categorized based on established clinical guidelines, which define a 5% weight change as clinically significant for metabolic improvements [26]. Thus, we categorized participants into three groups: weight loss (<−5%), weight maintenance (−5% to 5%), or weight gain (>5%). Participants who attempted weight loss were asked how they tried to lose weight. Participants were defined as using diet modification if they reported any change to diet (e.g., ate fewer calories, skipped eating occasions, followed a special diet, etc.).

2.4. Adiposity

Body weight, standing height, and waist circumference were measured by trained technicians using a digital scale, a stadiometer, and a measuring tape, respectively. BMI was computed as weight (kg) divided by height squared (m^2). BMI classifications followed the World Health Organization criteria, defining normal weight (18.5–24.9), overweight (25.0–29.9), and obesity ($\geq$30.0 kg/m^2) [27]. To address the limitation of BMI in differentiating between fat and lean mass, we additionally included abdominal obesity. Abdominal obesity was treated as a binary variable, defined as a waist circumference >88 cm for women and >102 cm for men.

2.5. Covariates and Demographic Characteristics

Demographic characteristics included self-reported age, sex, race, employment status, income, education level, and marital status. They were collected through questionnaires administered by trained interviewers during home visits. Income was categorized into three groups based on the ratio of family income to the poverty threshold: low (PIR < 1), middle (1 ≤ PIR < 4), and high (PIR ≥ 4) [28]. Smoking status was determined based on serum cotinine concentration, with levels exceeding 10 ng/mL classified as current smokers, while levels below this threshold indicated non-smokers [29]. Alcohol consumption was categorized as 'no' for participants who had never consumed alcohol, whereas those who reported alcohol consumption were further classified as 'moderate' drinkers (men: ≤2 drinks/day, women: ≤1 drink/day) or 'heavy' drinkers (men: >2 drinks/day, women: >1 drink/day) based on their average weekly intake over the past 12 months [30]. Physical activity was assessed using the Global Physical Activity Questionnaire (GPAQ). Participants were categorized into two groups (yes/no) based on whether they met physical activity guidelines, defined as achieving at least 150 min of moderate-intensity or 75 min of vigorous-intensity activity per week or an equivalent combination [31].

2.6. Statistical Analysis

Descriptive statistics were assessed to characterize demographic characteristics and chrononutrition patterns, including means and standard deviations (SD), medians and interquartile ranges (IQR), and frequencies with percentages. The weighted sample size represented the estimated population in the U.S. corresponding to the participants included in the study. Group comparisons by weight loss attempt, weight change percentage, obesity, and abdominal obesity were conducted using *t*-tests, Wilcoxon rank-sum tests, Kruskal–Wallis rank-sum tests, and chi-square tests. All statistical analyses accounted for the complex multistage probability sampling design of NHANES. Since standardized thresholds for classifying chrononutrition patterns do not exist, we used latent profile analysis (LPA) to derive data-driven subgroups based on shared eating timing, eating frequency, and caloric distribution patterns. This approach allowed for the identification of conceptually meaningful profiles grounded in the observed data rather than relying on arbitrary or predefined cut points—an important strength of using LPA in this context. LPA was selected over traditional clustering methods (e.g., k-means, hierarchical clustering) because it allows for probabilistic classification of individuals into latent classes while accounting for measurement uncertainty. Models with 2 to 10 classes were evaluated to determine the optimal number of classes. Model selection was guided by both statistical and practical considerations, including the following: (1) Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC); (2) the Likelihood Ratio Test; (3) a minimum class size threshold of 5%; and (4) the interpretability of the identified classes. The survey package in R (version 4.4-2) was used to apply appropriate sampling weights and compute prevalence estimates [32]. The gtsummary package (version 2.0.3) was employed to generate descriptive tables [33]. The depmixS package (version 1.5-0) was used for latent profile analysis [34]. All statistical tests were two-tailed, and significance was determined at an alpha level of 0.05. Analyses were conducted using R version 4.4.1.

3. Results

Among the 5287 adults, 3100 (58.6%) did not attempt weight loss in the past year, while 2187 (41.4%) reported a weight loss attempt. Of those who attempted weight loss, 2107 (96.3%) reported making dietary modifications (Supplemental Figure S1). Weight loss attempts were more common among women than men (58% vs. 47%, $p < 0.001$) and those with obesity than without obesity (BMI: 31 vs. 26, $p < 0.001$; obesity prevalence: 52% vs. 27%, $p < 0.001$). Participants attempting weight loss had higher education levels (67% vs. 59% beyond high school, $p < 0.001$), were more likely to be employed full-time (46% vs. 39%, $p = 0.012$), and had higher income levels (48% vs. 37%, $p < 0.001$), compared to non-attempters. Regarding health behaviors, the weight loss attempt group had a lower smoking prevalence (14% vs. 28%, $p < 0.001$) but higher heavy alcohol consumption prevalence (47% vs. 41%, $p = 0.069$), were more physically active (67% vs. 62%, $p = 0.003$), and more sedentary (360 vs. 300 min, $p < 0.001$), compared to the non-attempt group (Table 1). While eating timing and frequency did not differ between the weight loss attempt and non-attempt groups, those who attempted weight loss had lower total energy intake (1966 vs. 2066 kcal, $p = 0.011$) and a higher diet quality score (52 vs. 50, $p < 0.001$) (Table 2) than non-attempters.

Table 1. Demographic and behavioral characteristics by weight loss attempt.

Characteristic	Overall N = 163,365,719	Yes N = 71,781,886	No N = 91,583,833	*p*-Value
Age, years	48 (33, 63)	47 (33, 61)	50 (33, 65)	0.094
Sex				<0.001
Men	78,633,894 (48%)	30,458,685 (42%)	48,175,209 (53%)	
Women	84,731,825 (52%)	41,323,202 (58%)	43,408,623 (47%)	
Race/ethnicity				0.2
Mexican American	13,997,151 (8.6%)	6,954,507 (9.7%)	7,042,643 (7.7%)	
Other Hispanic	11,550,021 (7.1%)	5,227,646 (7.3%)	6,322,375 (6.9%)	
Non-Hispanic White	103,831,510 (64%)	44,682,828 (62%)	59,148,682 (65%)	
Non-Hispanic Black	17,274,683 (11%)	7,154,829 (10.0%)	10,119,854 (11%)	
Other race—including multi-racial	16,712,355 (10%)	7,762,077 (11%)	8,950,278 (9.8%)	
Education				<0.001
Below high school	16,118,032 (10%)	5,059,558 (7.2%)	11,058,475 (13%)	
High school	43,121,968 (27%)	17,728,701 (25%)	25,393,267 (29%)	
Beyond high school	99,017,676 (63%)	47,225,856 (67%)	51,791,820 (59%)	
Body mass index, kg/m^2	28 (24, 33)	31 (27, 35)	26 (23, 30)	<0.001
Body mass index				<0.001
Underweight/normal	44,069,948 (28%)	9,916,797 (14%)	34,153,151 (39%)	
Overweight	53,967,360 (34%)	24,406,910 (34%)	29,560,450 (34%)	
Obesity	61,075,893 (38%)	37,130,451 (52%)	23,945,442 (27%)	
Working status				0.012
Not working	65,285,256 (41%)	25,677,404 (37%)	39,607,852 (44%)	
Part-time	26,377,973 (17%)	11,743,644 (17%)	14,634,329 (16%)	
Full-time	66,894,404 (42%)	31,697,998 (46%)	35,196,406 (39%)	
Income level				<0.001
Low	18,675,282 (13%)	6,436,910 (10%)	12,238,372 (15%)	
Middle	66,737,035 (46%)	26,884,782 (42%)	39,852,253 (48%)	
High	61,060,391 (42%)	30,780,549 (48%)	30,279,842 (37%)	
Partner				0.003
Married/partner	99,896,139 (63%)	47,069,118 (67%)	52,827,021 (60%)	
Single	58,394,728 (37%)	22,966,382 (33%)	35,428,346 (40%)	
Smoking status				<0.001
Current smoking	33,468,344 (22%)	9,761,175 (14%)	23,707,169 (28%)	
Non-smoking	120,716,609 (78%)	58,373,600 (86%)	62,343,009 (72%)	
Alcohol use				0.069
Heavy	58,113,097 (43%)	27,998,913 (47%)	30,114,184 (41%)	
Moderate	62,943,076 (47%)	27,207,829 (45%)	35,735,247 (48%)	
No	12,753,376 (9.5%)	4,901,736 (8.2%)	7,851,641 (11%)	
Physical activity, >150 min/wk	105,528,092 (65%)	48,411,171 (67%)	57,116,921 (62%)	0.003
Sedentary time, min/day	300 (180, 480)	360 (240, 480)	300 (180, 480)	<0.001

Median (Q1, Q3); N(%) design-based Kruskal–Wallis test; Pearson's X^2: Rao–Scott adjustment.

Table 2. Chrononutrition patterns by weight loss attempt.

Characteristic	Yes N = 71,781,886	No N = 91,583,833	*p*-Value
Hours between Waketime and First Eating [1]	1.64 (1.51)	1.71 (1.56)	0.3
Hours between Last Eating and Bedtime [1]	2.85 (2.00)	2.84 (1.99)	>0.9
Hours between Awake Midpoint and 50% Caloric Point [1]	0.48 (2.62)	0.54 (2.69)	0.6
Eating Window, h [1]	11.96 (2.27)	11.91 (2.27)	0.6
Number of Eating Episodes [1]	5.38 (1.71)	5.24 (1.58)	0.13
Number of Main Meal Episodes [1]	2.55 (0.77)	2.53 (0.77)	0.7
Frequency of Snack [1]	3.05 (1.69)	2.92 (1.58)	0.12
Frequency of Nighttime Snack [2]	0.50 (0.00, 1.00)	0.50 (0.00, 1.00)	0.5
% of Total Kcal <2 h of Waketime [2]	8 (0, 19)	7 (0, 20)	0.7
% of Total Kcal >2 h of Waketime and Waking Midpoint [2]	38 (26, 49)	38 (26, 49)	0.7
% of Total Kcal Waking Midpoint to >2 h of Bedtime [2]	46 (35, 58)	46 (34, 58)	0.8
% of Total Kcal <2 h of Bedtime [2]	0 (0, 9)	0 (0, 12)	0.031
Having Breakfast [3]	59,919,069 (83%)	77,601,179 (85%)	0.4
Having Lunch [3]	58,691,905 (82%)	73,223,050 (80%)	0.3
Having Dinner [3]	56,010,160 (78%)	68,993,057 (75%)	0.2
Having Snack [3]	69,865,821 (97%)	89,156,217 (97%)	>0.9
Total Kcal [1]	1966 (779)	2066 (834)	0.011
Health Eating Index [1]	52 (12)	50 (13)	<0.001

[1] Mean (SD); design-based *t*-test. [2] Median (Q1, Q3); design-based Wilcoxon rank-sum test.[3] N(%); Pearson's X^2: Rao–Scott adjustment.

3.1. Chrononutrition Profiles

We identified four distinct chrononutrition profiles: Typical Eating, Early Eating, Later Eating, and Extended Eating Window. The Typical Eating profile, representing the most common pattern, had its first eating episode 1.57 h (SD = 0.99) after waking, consumed its last eating 2.91 h (SD = 1.16) before bedtime, and had an average eating window of 11.78 h (SD = 1.05). Their caloric midpoint occurred close to the awake midpoint (0.20 h, SD = 2.55). Compared to the Typical Eating, the Early Eating profile stopped eating much earlier before bedtime (7.17 h, SD = 2.30), resulting in a shorter eating window of 9.50 h (SD = 2.48) and earlier caloric midpoint (1.06 h before the awake midpoint, SD = 2.49). In contrast, the Later Eating profile delayed their first eating episode substantially (5.52 h, SD = 1.85) and had 3.17 h (SD = 1.96) between their last eating and bedtime, with the shortest eating window of 7.97 h (SD = 3.03) and the latest caloric midpoint (2.04 h after the awake midpoint, SD = 2.57). Lastly, The Extended Eating Window profile started eating sooner after waking (0.81 h, SD = 0.62) and continued eating until closer to bedtime (1.24 h, SD = 0.69), resulting in the longest eating window of 14.16 h (SD = 1.05) (Table 3).

Table 3. Chrononutrition patterns by chrononutrition profiles.

Characteristic	Typical Eating N = 39,331,668	Early Eating N = 6,037,501	Later Eating N = 4,852,869	Extended Eating Window N = 19,561,923
Hours between Waketime and First Eating	1.57 (0.99)	1.67 (1.28)	5.52 (1.85)	0.81 (0.62)
Hours between Last Eating and Bedtime	2.91 (1.16)	7.17 (2.30)	3.17 (1.96)	1.24 (0.69)
Hours between Awake Midpoint and 50% Caloric Point	0.20 (2.55)	−1.06 (2.49)	2.04 (2.57)	1.18 (2.39)
Eating Window	11.78 (1.05)	9.50 (2.48)	7.97 (3.03)	14.16 (1.05)

Mean (SD).

3.2. Chrononutrition Patterns by Weight Change Status

Next, we examined how chrononutrition patterns varied by weight change status. Participants who gained weight (vs. loss) had a 0.16 h longer duration between waking and first eating (1.78 vs. 1.62 h, $p = 0.024$), a 9% lower proportion of total caloric intake occurring later in the day (43% vs. 52%, $p < 0.001$) and 0.23 fewer eating episodes (5.20 vs. 5.43, $p = 0.008$). Additionally, the weight maintenance group (vs. loss) had a 4% higher prevalence of breakfast (86% vs. 82%, $p = 0.069$) but a 4% lower prevalence of dinner (76% vs. 80%, $p = 0.055$) consumption. The Extended Eating Window profile was more common among those who maintained or gained weight than those who lost weight (31% and 24%, respectively vs. 12%, $p = 0.068$) (Table 4).

Table 4. Chrononutrition patterns by weight change status.

Characteristic	Weight Loss N = 2,374,492 [1]	Weight Maintenance N = 45,903,898 [1]	Weight Gain N = 20,104,228 [1]	*p*-Value
Hours between Waketime and First Eating [1]	1.62 (1.50)	1.57 (1.48)	1.78 (1.49)	0.024
Hours between Last Eating and Bedtime [1]	2.92 (1.35)	2.83 (2.04)	2.79 (1.91)	0.5
Hours between Awake Midpoint and 50% Caloric Point [1]	0.28 (2.67)	0.60 (2.51)	0.34 (2.77)	0.7
Eating Window, h [1]	11.68 (1.98)	12.09 (2.27)	11.86 (2.22)	0.2
Number of Eating Episodes [1]	5.43 (1.66)	5.50 (1.77)	5.20 (1.52)	0.008
Number of Main Meal Episodes [1]	2.46 (0.77)	2.55 (0.79)	2.55 (0.71)	0.8
Frequency of Snack [1]	3.12 (1.53)	3.16 (1.73)	2.88 (1.58)	0.10
Frequency of Nighttime Snack [2]	0.50 (0.00, 1.00)	0.50 (0.00, 1.00)	0.50 (0.00, 1.00)	0.6
% of Total Kcal <2 h of Waketime [2]	11 (0, 19)	8 (0, 18)	7 (0, 19)	0.5
% of Total Kcal >2 h of Waketime and Waking Midpoint [2]	30 (13, 48)	37 (26, 48)	39 (29, 51)	0.2
% of Total Kcal Waking Midpoint to >2 h of Bedtime [2]	52 (43, 68)	47 (35, 58)	43 (34, 55)	<0.001
% of Total Kcal <2 h of Bedtime [2]	0 (0, 6)	0 (0, 10)	0 (0, 10)	>0.9
Having Breakfast [3]	1,940,134 (82%)	39,289,111 (86%)	16,088,521 (80%)	0.069
Having Lunch [3]	1,884,341 (79%)	37,932,845 (83%)	16,436,620 (82%)	0.8
Having Dinner [3]	1,894,735 (80%)	34,859,309 (76%)	16,546,231 (82%)	0.055
Having Snack [3]	2,374,492 (100%)	44,740,605 (97%)	19,651,224 (98%)	0.5
Total Kcal [1]	1974 (782)	1994 (771)	1903 (762)	0.2
Health Eating Index [1]	54 (12)	53 (12)	50 (12)	0.014
Chrononutrition Profile [3]				0.068
Early Eating	227,854 (9.6%)	3,655,293 (8.0%)	2,022,425 (10%)	
Extended Eating Window	285,684 (12%)	14,250,093 (31%)	4,861,106 (24%)	
Later Eating	188,937 (8.0%)	2,952,477 (6.4%)	1,581,425 (7.9%)	
Typical Eating	1,672,016 (70%)	25,046,035 (55%)	11,639,272 (58%)	

[1] Mean (SD); design-based *t*-test. [2] Median (Q1, Q3); design-based Wilcoxon rank-sum test. [3] N (%); Pearson's X^2: Rao–Scott adjustment.

3.3. Chrononutrition Patterns by Obesity Status

Individuals with obesity (vs. under/normal weight) had a 0.51 h delay in first eating (1.80 vs. 1.29 h, $p < 0.001$) and a 0.45 h shorter eating window (11.77 vs. 12.22 h, $p = 0.020$), whereas those with normal weight had 0.81 more eating episodes (5.97 vs. 5.16, $p < 0.001$), including both main meals and snacks. Similarly, the prevalence of eating breakfast (91%

vs. 80%, $p < 0.001$), lunch (90% vs. 78%, $p = 0.005$), and dinner (89% vs. 75%, i = 0.001) was highest in the normal weight group and lowest in the obesity group. The Extended Eating Window profile was 9% less common among those with obesity compared to those with under/normal weight (24% vs. 33%), whereas the Later Eating profile was 2.7% more common (8.3% vs. 5.6%; $p = 0.063$). The Early Eating profile had a lower prevalence in the overweight group (7.6%) compared to the normal weight and obesity groups (9.3% and 9.2%, respectively) (Table 5).

Table 5. Chrononutrition patterns by BMI.

Characteristic	Underweight/Normal N = 9,511,853	Overweight N = 23,768,388	Obesity N = 36,175,991	*p*-Value
Hours between Waketime and First Eating [1]	1.29 (1.31)	1.53 (1.31)	1.80 (1.64)	<0.001
Hours between Last Eating and Bedtime [1]	2.75 (1.65)	2.69 (1.89)	2.94 (2.13)	0.2
Hours between Awake Midpoint and 50% Caloric Point [1]	0.31 (2.36)	0.51 (2.61)	0.53 (2.67)	0.3
Eating Window, h [1]	12.22 (2.02)	12.25 (2.02)	11.77 (2.43)	0.020
Number of Eating Episodes [1]	5.97 (1.88)	5.55 (1.55)	5.16 (1.73)	<0.001
Number of Main Meal Episodes [1]	2.80 (0.66)	2.64 (0.75)	2.41 (0.77)	<0.001
Frequency of Snack [1]	3.29 (1.69)	3.19 (1.66)	2.95 (1.72)	0.036
Frequency of Nighttime Snack [2]	0.50 (0.00, 1.00)	0.50 (0.00, 1.00)	0.50 (0.00, 1.00)	0.3
% of Total Kcal <2 h of Waketime [2]	9 (0, 20)	8 (0, 18)	7 (0, 19)	0.3
% of Total Kcal >2 h of Waketime and Waking Midpoint [2]	39 (24, 48)	37 (27, 48)	38 (26, 50)	>0.9
% of Total Kcal Waking Midpoint to >2 h of Bedtime [2]	45 (36, 57)	47 (36, 57)	46 (34, 58)	0.5
% of Total Kcal <2 h of Bedtime [2]	0 (0, 12)	0 (0, 10)	0 (0, 9)	0.8
Having Breakfast [3]	8,672,109 (91%)	20,387,578 (86%)	28,951,429 (80%)	<0.001
Having Lunch [3]	8,560,195 (90%)	19,998,057 (84%)	28,321,735 (78%)	0.005
Having Dinner [3]	8,436,761 (89%)	18,420,479 (77%)	27,150,005 (75%)	0.001
Having Snack [3]	9,352,806 (98%)	23,574,755 (99%)	34,738,703 (96%)	0.002
Total Kcal [1]	1856 (671)	2004 (734)	1961 (809)	0.3
Health Eating Index [1]	56 (12)	54 (12)	50 (12)	<0.001
Chrononutrition Profile [3]				0.063
Early Eating	883,820 (9.3%)	1,799,088 (7.6%)	3,328,882 (9.2%)	
Extended Eating Window	3,116,765 (33%)	7,725,655 (33%)	8,674,361 (24%)	
Later Eating	528,284 (5.6%)	1,215,364 (5.1%)	2,993,385 (8.3%)	
Typical Eating	4,982,984 (52%)	13,028,282 (55%)	21,179,363 (59%)	

[1] Mean (SD); design-based *t*-test. [2] Median (Q1, Q3); design-based Wilcoxon rank-sum test. [3] N(%); Pearson's X^2: Rao–Scott adjustment.

Participants with abdominal obesity consumed a 2% greater proportion of their total caloric intake later in the day (47% vs. 45%, $p = 0.012$). However, individuals without abdominal obesity had 0.27 more main meals (2.73 vs. 2.46, $p < 0.001$) and a higher prevalence of eating breakfast (87% vs. 82%, $p = 0.010$), lunch (89% vs. 79%, $p = 0.003$), and dinner (85% vs. 75%, $p = 0.006$). The Early Eating and Extended Eating Window profiles were less common among individuals with abdominal obesity compared to those without (Early Eating: 7.9% vs. 10% and Extended Eating Window: 26% vs. 34%, $p = 0.024$) (Table 6).

Table 6. Chrononutrition patterns by abdominal obesity.

Characteristic	Non-Obesity N = 20,964,970	Obesity N = 48,818,991	p-Value
Hours between Waketime and First Eating [1]	1.52 (1.49)	1.69 (1.52)	0.10
Hours between Last Eating and Bedtime [1]	2.81 (1.93)	2.83 (2.01)	>0.9
Hours between Awake Midpoint and 50% Caloric Point [1]	0.44 (2.54)	0.52 (2.63)	0.7
Eating Window, h [1]	12.09 (2.25)	11.94 (2.26)	0.3
Number of Eating Episodes [1]	5.56 (1.70)	5.33 (1.72)	0.2
Number of Main Meal Episodes [1]	2.73 (0.72)	2.46 (0.77)	<0.001
Frequency of Snack [1]	3.03 (1.58)	3.09 (1.75)	0.6
Frequency of Nighttime Snack [2]	0.50 (0.00, 1.00)	0.50 (0.00, 1.00)	0.3
% of Total Kcal <2 h of Waketime [2]	8 (0, 19)	7 (0, 18)	0.14
% of Total Kcal >2 h of Waketime and Waking Midpoint [2]	38 (27, 48)	37 (26, 50)	>0.9
% of Total Kcal Waking Midpoint to >2 h of Bedtime [2]	45 (33, 54)	47 (35, 59)	0.012
% of Total Kcal <2 h of Bedtime [2]	0 (0, 12)	0 (0, 9)	0.2
Having Breakfast [3]	18,273,959 (87%)	39,959,542 (82%)	0.010
Having Lunch [3]	18,554,603 (89%)	38,618,732 (79%)	0.003
Having Dinner [3]	17,844,507 (85%)	36,417,642 (75%)	0.006
Having Snack [3]	20,530,340 (98%)	47,463,652 (97%)	0.5
Total Kcal [1]	2043 (776)	1927 (763)	0.051
Health Eating Index [1]	55 (13)	51 (12)	0.002
Chrononutrition Profile [3]			0.024
Early Eating	2,173,719 (10%)	3,863,782 (7.9%)	
Extended Eating Window	7,041,269 (34%)	12,520,655 (26%)	
Later Eating	1,496,916 (7.1%)	3,355,953 (6.9%)	
Typical Eating	10,253,067 (49%)	29,078,602 (60%)	

[1] Mean (SD); design-based *t*-test. [2] Median (Q1, Q3); design-based Wilcoxon rank-sum test. [3] N(%); Pearson's X^2: Rao–Scott adjustment.

4. Discussion

Despite increasing recognition of chrononutrition's role in weight management, its patterns among U.S. adults who recently attempted weight loss remain understudied. This study addresses this knowledge gap. The results show that the most common chrononotu-rition profile among weight loss attempters was the Typical Eating group, characterized by balanced eating timing, a moderate eating window, and a well-aligned caloric midpoint. Although the observed difference in total caloric intake between weight loss attempters and non-attempters was modest (approximately 100 kcal), prior research suggests that even small daily reductions in energy intake can be clinically meaningful for weight management and the prevention of gradual weight gain over time [35,36]. Individuals with favorable body weight profiles, including those who lost or maintained weight and had a normal BMI and healthy waist circumference, were more likely to consume frequent meals and snacks and follow structured meal patterns with breakfast, lunch, and dinner. In contrast, participants who gained weight, had a BMI of >30 kg/m^2, or had abdominal obesity were more likely to delay their first eating after waking, have fewer eating episodes, and exhibit extended eating windows closer to bedtime. These findings underscore the importance of integrating chrononutrition strategies into traditional weight loss interventions focused on dietary modifications and physical activity to enhance their effectiveness.

This study's findings are novel as they provide the first comprehensive characterization of chrononutrition patterns across different weight loss and obesity groups in a nationally representative sample of U.S. adults. Notably, this study builds upon the work of Farsijani et al., the only research to date that examined 15 years of chrononutrition trends in the NHANES 2003–2018 population [37]. Farsijani et al. reported persistent trends in late-day energy consumption among American adults, with dinner contributing the highest proportion of daily intake, widespread late-night eating, and prolonged eating windows exceeding 13 h. Building on these findings, our analysis further introduced distinct chrononutrition profiles—Typical Eating, Early Eating, Later Eating, and Extended Eating Window—offering a more nuanced understanding of eating patterns. By analyzing the the intervals between waketime, bedtime, and eating timing, weight loss attempters were grouped into profiles that appeared most frequently in the following order: Typical Eating, Extended Eating Window, Early Eating, and Later Eating. Typical Eating, the most prevalent profile, showed a relatively even distribution across eating timing. Extended Eating Window, the second most common, was marked by an early start to eating after waking and a late end to eating before bed, resulting in the longest eating duration. Early Eating consumed half of their daily calories during the earlier hours of the day and had a long fasting period before bedtime. Later Eating, the least represented group, showed a noticeably delayed eating onset and tended to consume most of their calories later in the day. These profiles represent prototypical chrononutrition patterns among weight loss attempters in the U.S. and provide a framework for identifying key behavioral features, offering valuable insights that can inform more personalized and targeted weight management strategies. These findings highlight a critical gap between emerging research on chrononutrition and current weight loss strategies used by adults, which primarily emphasize diet quality and caloric restriction without addressing eating timing. Further stratification of chrononutrition behaviors by weight loss and obesity groups showed that cardiometabolically unfavorable groups—those who gained weight or had obesity—tended to delay their first eating longer after waking, had fewer eating episodes, and exhibited more irregular eating patterns compared to their metabolically healthier counterparts. This finding may suggest the need to increase public awareness about the importance of when individuals eat—alongside **what** and **how much** they eat—to achieve successful weight loss. It is also possible that such patterns may result from other factors or reflect consequences of excess weight gain rather than causes. For instance, individuals experiencing higher levels of stress may skip or delay eating and eat irregularly due to disrupted routines or emotional coping mechanisms. Similarly, poor sleep patterns—such as short sleep duration, late sleep timing, or sleep disturbances—can alter appetite-regulating hormones and shift eating behaviors toward later or more erratic patterns. In addition, varying work schedules, including night shifts or long work hours, may limit opportunities for regular eating and lead to delayed or reduced eating frequency. These alternative explanations could also be considered when interpreting the observed associations between eating patterns and metabolic status, as the relationship may be bidirectional.

Our findings align with prior research highlighting the negative impact of irregular eating patterns. For instance, Akbar et al. found that unfavorable midpoint eating times, eating occasion skipping, and shift work were associated with an increased risk of Circadian Syndrome, emphasizing the importance of structured eating timing in mitigating circadian disruptions [38]. Similarly, Raji et al. reported that earlier and more consistent eating timing may promote cardiometabolic health [39]. Numerous other studies have demonstrated the critical role of eating timing in metabolic regulation through its interaction with the circadian clock, and related dietary approaches, such as intermittent fasting and time-restricted feeding (TRF), are also actively being investigated [14,40–45]. While the evidence is still evolving, several randomized controlled trials and observational studies have reported that TRF and intermittent fasting may support weight loss and improve metabolic markers, particularly when eating windows are aligned with the body's natural circadian rhythm [40,41,43]. Taken together, our findings reinforce the potentially significant influence of chrononutrition factors on cardiometabolic health. Further research is needed to develop effective, evidence-based dietary interventions that integrate chrononutrition principles to promote healthy weight management.

Several limitations should be considered when interpreting this study's results. First, this study examines only current chrononutrition patterns, which may not represent participants' behaviors before or during their weight loss attempts. However, the findings provide a starting point for generating hypotheses in future research. For example, our findings suggest a potential relationship between obesity and the duration between waketime and first eating, as well as a shorter overall eating window. Future research should explore the underlying factors driving these patterns. One possibility is that psychological factors, such as stress or food avoidance behaviors, may also contribute to delayed intake [46,47]. Additionally, socioeconomic and lifestyle constraints—such as work schedules, caregiving responsibilities, or shift work—could shape these eating behaviors. These contextual factors may influence both eating timing and weight status, making it challenging to disentangle the independent effect of chrononutrition from other social determinants of health. For instance, individuals with nonstandard work hours or caregiving demands may have limited flexibility in eating timing, potentially leading to delayed or irregular eating patterns, and these socioeconomic and lifestyle constraints may also be associated with obesity. Despite these limitations, the observed chrononutrition patterns offer valuable insights into real-world eating behaviors across diverse groups. These findings provide a useful foundation for generating hypotheses and guiding the design of future, more targeted interventions. Future studies should incorporate more detailed measurements of these variables to better account for their potential confounding effects. Longitudinal studies and experimental designs are also needed to assess the causal mechanisms underlying these associations and to determine whether modifying eating timing can improve weight loss outcomes and metabolic health. Moreover, reliance on self-reported prior weight may introduce recall bias, which could affect the validity of weight change classification. The 24 h dietary recall method may also be subject to recall and social desirability bias. However, it has been extensively validated in prior studies using the USDA Automated Multiple Pass Method and provides reliable estimates of group-level energy and nutrient intake [48,49]. In addition, while we classified participants as physically active based on WHO recommendations ($\geq$150 min of moderate or $\geq$75 min of vigorous activity per week), lower levels of physical activity may still provide health benefits [50]. Therefore, our use of this binary cutoff may have underestimated the beneficial effects of sub-threshold activity levels. Lastly, obesity in this study was classified using BMI cutoffs. While BMI provides clinically standardized and widely accepted thresholds for underweight, overweight, and obesity that facilitate comparisons across studies, it does not differentiate between fat mass and lean body mass. To address this limitation, we also incorporated abdominal obesity, defined by waist circumference, as a more specific indicator of central adiposity and cardiometabolic risk.

Despite these limitations, this study has notable strengths. To our knowledge, this is the first study to characterize chrononutrition patterns among a nationally representative sample of U.S. adults who attempted weight loss in the past year. These findings could have meaningful implications for developing personalized, precision-based weight management strategies. Moreover, the stratification by age and sex allows for a more detailed understanding of chrononutrition patterns across different demographic groups. Lastly, the study's focus on timing relative to sleep—such as the duration between waking and first eating—provides a novel perspective on the relationship between eating timing and weight management.

5. Conclusions

In conclusion, the weight gain group had delayed first eating, fewer eating episodes, and earlier caloric intake. Individuals with obesity had shorter eating windows, delayed eating, and lower eating frequency. Similarly, those with abdominal obesity exhibited delayed high-calorie intake and lower eating frequency. The Extended Eating Window profile was more common in weight maintenance and gain groups, whereas non-obese individuals favored Early Eating patterns. These findings suggest that chrononutrition patterns may play a role in developing personalized weight management strategies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/dietetics4020024/s1, Figure S1: Study Population Flow Chart.

Author Contributions: N.K.: Conceptualization, methodology, formal analysis, data curation, writing—original draft preparation, visualization; H.J.: writing—original draft preparation, M.H.: Conceptualization, methodology, validation, supervision; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The NHANES study procedures were conducted in accordance with the Declaration of Helsinki and approved by the National Center for Health Statistics Ethics Review Board, 26 October 2017 (Protocol #2018-01).

Informed Consent Statement: Informed consent was obtained from all participants involved in the NHANES.

Data Availability Statement: The original data presented in the study are openly available in the NHANES.

Conflicts of Interest: The authors declare no conflicts of interest.

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