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Food-Ordering Application Use, Dietary Total Sugars Intake, and Cardiometabolic Risk Markers Among Working-Age Adults: A Cross-Sectional Study in Chiang Mai, Thailand

Wason Parklak [1,2], Hataichanok Chuljerm [1,2], Anupon Iadnut [3], Puriwat Fakfum [2], Putita Jiraya [1], Praporn Kijkuokool [2], Wiritphon Khiaolaongam [2], Surasawadee Somnuk [4] and Kanokwan Kulprachakarn [1,2,*]

1 Research Institute for Health Sciences, Chiang Mai University, Chiang Mai 50200, Thailand; wason.p@cmu.ac.th (W.P.); hataichanok.ch@cmu.ac.th (H.C.); putita_jiraya@cmu.ac.th (P.J.)
2 School of Health Sciences Research, Research Institute for Health Sciences, Chiang Mai University, Chiang Mai 50200, Thailand; puriwat_f@cmu.ac.th (P.F.); praporn_k@cmu.ac.th (P.K.); itthichai.khiao@cmu.ac.th (W.K.)
3 Faculty of Medicine, Nation University, Chiang Mai 50210, Thailand; anupon_iad@nation.ac.th
4 Department of Sports Science, Faculty of Sports and Health Science, Kamphaeng Saen Campus, Kasetsart University, Nakhon Pathom 73140, Thailand; surasawadee.so@ku.th
* Correspondence: kanokwan.kul@cmu.ac.th

Abstract

Background/Objectives: This study examined associations between food-ordering application use, dietary intake, and cardiometabolic markers among working-age adults in Chiang Mai, Thailand. **Methods:** This exploratory cross-sectional study included 94 volunteers aged 30 to <60 years from a single local government workplace. Reported ordering frequency during the preceding month was assessed by interview. Anthropometric, body composition, and fasting biochemical measures were obtained. Dietary intake was averaged across three 24-h recalls. Four frequency categories were examined using regression models adjusted for age, sex, education, physical activity, household income, and total energy intake. Benjamini–Hochberg correction was applied across 39 overall outcome tests. **Results:** Thirty-nine participants reported ordering at least monthly, and 55 reported less frequent ordering or no use. In unadjusted comparisons, the ≥1/month group had higher body mass index (28.39 versus 24.08 kg/m^2), median total sugars intake (47.69 versus 21.27 g/day), and median homeostatic model assessment of insulin resistance (HOMA-IR; 2.23 versus 1.24; all $p < 0.001$), and lower median dietary fiber intake (9.48 versus 14.66 g/day; $p = 0.009$). Adjusted overall associations met the false discovery rate threshold for body mass index, related adiposity measures, fasting insulin, HOMA-IR, total sugars intake, and dietary fiber intake (all $q < 0.05$). **Conclusions:** Food-ordering application use frequency was associated with total sugars and dietary fiber intake, adiposity measures, and HOMA-IR in this workplace sample. These findings support further investigation of food-ordering behaviors in relation to dietary intake and cardiometabolic health.

Keywords: food-ordering applications; total sugars; dietary fiber; body composition; adiposity; insulin resistance; cardiometabolic markers; Chiang Mai; Thailand

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1. Introduction

The COVID-19 pandemic accelerated changes in how consumers obtained prepared meals, making food-ordering applications a familiar part of the food environment. These

platforms allow users to browse a wide range of meals and beverages and order them with little time or effort [1–3]. Although changes in app use during the pandemic were not uniform across countries, food-ordering application services remain relevant to food purchasing in Thailand and are available in provincial areas beyond Bangkok [4–6]. This wider reach raises an important public health question: whether easier access to prepared food is accompanied by differences in overall dietary intake and cardiometabolic health [4,7].

The nutritional quality of foods offered through food-ordering application platforms warrants attention. In Bangkok, Jindarattanaporn et al. analyzed popular items available through major delivery applications and found that many ready-to-eat meals were high in sodium, while several desserts contained substantial amounts of sugar [4]. More recently, a Malaysian study catalogued 3729 foods and 1882 beverages available on food delivery platforms. Among the selected common items evaluated using a nutrient profiling system, 15 of 23 foods and 19 of 24 beverages were classified as less healthy [8].

Evidence relating food-ordering application use to individual health outcomes is growing but remains mixed. A 2024 study in England found an association between takeaway delivery app use and obesity [9], whereas a 2025 study of Malaysian civil servants found no association between frequent food-ordering application use and overweight or obesity [10]. The Malaysian study also reported that coffee and sugar-sweetened beverages were commonly ordered with meals [10]. A systematic review of studies conducted during the COVID-19 pandemic reported associations between meal delivery app use and outcomes such as weight gain and less favorable eating behaviors in some studies, while emphasizing the limited evidence and the need for further research [11].

Examining diet and health measures together may provide a more informative picture than examining body mass index (BMI) alone. High intake of sodium, sugars, and saturated fat, together with inadequate consumption of fiber-rich foods, is relevant to noncommunicable disease prevention [12,13]. Excess sodium is associated with elevated blood pressure [14], while an intervention study found greater visceral fat accumulation following sustained consumption of sugar-sweetened beverages than following consumption of comparison drinks [15]. Body fat distribution and cardiometabolic markers, including measures of insulin resistance and blood lipids, may provide information beyond BMI alone [16,17]. Nutritional analyses of foods available through delivery applications provide a rationale for studying food-ordering application use [4,8]. However, evidence about available menu items does not establish what individual users consume or whether application use causes metabolic changes.

Existing evidence includes nutritional analyses of foods offered through delivery applications in Bangkok [4], but associations between food-ordering application use, overall dietary intake, and measured cardiometabolic markers warrant further investigation among working adults outside major metropolitan settings. Assessing dietary intake, body composition, and fasting biochemical markers in the same participants may help characterize these associations. Therefore, this exploratory cross-sectional study compared dietary intake, anthropometric and body composition measures, and fasting biochemical markers between adults reporting food-ordering application use at least once per month and those reporting less frequent use or no use at a local government workplace in Mae Taeng District, Chiang Mai, Thailand. Associations between reported ordering-frequency categories and study outcomes were also examined across all participants.

2. Materials and Methods

2.1. Ethics Approval and Informed Consent

The study protocol was approved by the Human Experimentation Committee of the Research Institute for Health Sciences, Chiang Mai University, Thailand, on 30 January 2025 (approval certificate No. 03/2025). Before enrollment, the research team explained

the study objectives, procedures, potential benefits, and foreseeable risks to prospective participants. Written informed consent was obtained from all participants before any study data were collected.

2.2. Study Design and Participants

This exploratory cross-sectional study recruited adults aged 30 to <60 years who worked at a single local government workplace in San Maha Phon Subdistrict, Mae Taeng District, Chiang Mai, Thailand. Recruitment was coordinated through the director of the workplace's public health division. Study information was publicized internally, and interested employees volunteered for eligibility screening. Participants were therefore recruited through voluntary, non-probability sampling. Individuals were ineligible if they had a severe physician-diagnosed medical condition that could affect participation or the study measurements, including cardiovascular disease, renal failure, active infection, liver disease, gout, cancer, thalassemia, or a condition requiring postoperative care. Pregnancy, breastfeeding, and conditions that could substantially impair participation, such as severe psychiatric illness or alcohol or drug dependence, were additional exclusion criteria. Individuals who declined participation or withdrew consent were not included.

The target sample size for the broader survey of dietary behaviors and metabolic health was 91 participants. This was calculated using a population proportion formula with finite population correction, assuming a population of 5005 adults, a proportion of 0.60, a 95% confidence level, and an absolute precision of 0.10. The final analytical sample comprised 94 participants. The sample size calculation was not specifically designed for comparisons between application-use groups or for multivariable analyses; these analyses were considered exploratory.

Of 96 individuals assessed for eligibility, two were excluded: one had an active infection and one did not meet another eligibility criterion. The final analysis included 94 participants. Based on self-reported food-ordering application use, 39 participants reported ordering at least once per month, and 55 reported ordering less than once per month, including no use (Figure 1).

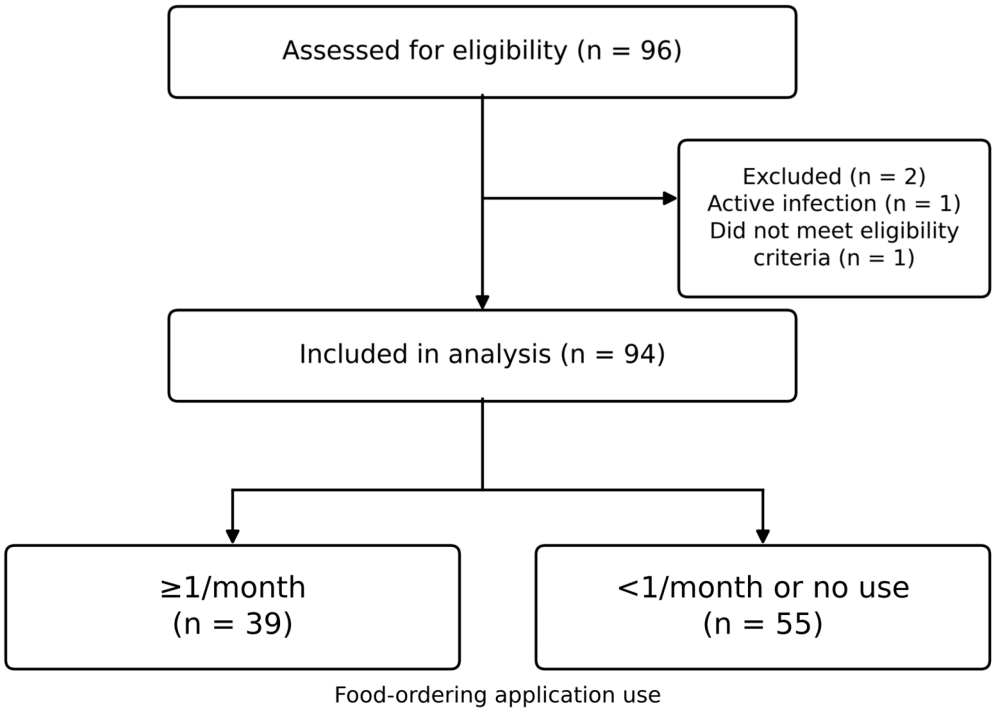


Figure 1. Flow diagram of participant screening and inclusion in the analysis.

2.3. Data Collection and Measurements

Data were collected between July and August 2025 at the participating workplace. Participants were instructed to fast for at least 10 h before blood collection and body composition assessment and to avoid strenuous exercise for 48 h before the study visit. Trained research personnel measured height, weight, waist circumference, and hip circumference. Body mass index was calculated as weight in kilograms divided by height in meters squared. Waist-to-hip ratio was calculated as measured waist circumference divided by measured hip circumference. Waist-to-height ratio was calculated as measured waist circumference divided by height, with both measurements expressed in centimeters.

Body composition was estimated using bioelectrical impedance analysis (BIA) with a Mediana i55 analyzer (MEDIANA Co., Ltd., Wonju, Republic of Korea). Measurements were performed in the fasting state after approximately 10–15 min of rest. Device-derived estimates included body fat mass, body fat percentage, visceral fat area, and subcutaneous fat area. The visceral-to-subcutaneous fat ratio was calculated by dividing the device-estimated visceral fat area by the device-estimated subcutaneous fat area.

Blood pressure was measured twice using an automated upper-arm monitor (OMRON JPN500; OMRON HEALTHCARE Co., Ltd., Muko, Kyoto, Japan), with a 10-min interval between measurements. The mean of the two readings was used in the analysis. Fasting blood glucose, lipid concentrations, and insulin were analyzed by BRIA Lab, Chiang Mai, Thailand. The homeostasis model assessment of insulin resistance (HOMA-IR) was calculated as fasting glucose (mg/dL) multiplied by fasting insulin (μIU/mL) and divided by 405 [18]. HOMA-IR was used as an indirect index of insulin resistance.

A structured case record form captured participant characteristics, including age, sex, educational attainment, marital status, and household income.

Food-ordering application use was assessed through a structured interview in which participants were asked to recall their ordering behavior during the month preceding the interview. The assessment covered applications used to order food and beverages, including food delivery platforms, convenience store or supermarket applications, and restaurant applications. Participants were classified into two groups according to their reported ordering frequency: at least once per month ($n = 39$) and less than once per month, including no use ($n = 55$). The four categories used in the frequency analysis were less than once per month, including no use; once per month; 2–3 times per month; and 2–3 times per week. Ordering frequency was assessed across application types, while the primary application type was recorded separately as the single category used most frequently. Participants ordering at least once per month also reported their usual ordering times, commonly ordered food and beverage categories, restaurant-selection criteria, and reasons for application use. Multiple responses were permitted for ordering times, and up to three responses were permitted for each of the other preference questions.

Physical activity during the preceding seven days was assessed using the Thai International Physical Activity Questionnaire–Short Form (IPAQ-SF) [19]. Following the IPAQ scoring protocol, durations below 10 min/day were recoded to zero and durations above 180 min/day were truncated to 180 min/day for each activity category. Walking, moderate-intensity activity, and vigorous-intensity activity were assigned 3.3, 4.0, and 8.0 METs, respectively. Category scores were calculated as METs × minutes/day × days/week and summed as total MET-min/week. Sitting time was excluded from the total score.

2.4. Dietary Assessment

Dietary intake was assessed through face-to-face interviews covering three consecutive 24-h periods, comprising two weekdays and one weekend day [20,21]. Approximately one week before the interviews, participants were encouraged to document or photograph the

foods and beverages consumed on the designated days to support recall. Trained research personnel used a standardized form and household items, including plates, bowls, cups, and spoons, to assist with portion-size estimation. The assessment covered foods and beverages consumed from all sources.

Energy and nutrient intakes were calculated using INMUCAL–Nutrients version 4.0 (Institute of Nutrition, Mahidol University, Nakhon Pathom, Thailand). For each participant, the three daily estimates were averaged to obtain one mean daily intake value for each dietary variable. Sugars intake was reported as total sugars; naturally occurring sugars, added sugars, and free sugars were not quantified separately. Individual foods and beverages reported in the recalls were not linked to specific application-based purchases.

2.5. Statistical Analysis

Analyses were performed using Python 3.12 with NumPy 2.3.5, SciPy 1.17.0, and pandas 2.2.3. Categorical variables are presented as n (%) and were compared using Pearson's chi-square test or conditional Monte Carlo chi-square tests for sparse tables. Continuous distributions were assessed using the Shapiro–Wilk test. Variables summarized as mean ± standard deviation were compared using Welch's t test, and those summarized as median (Q1–Q3) using two-sided Mann–Whitney U tests. Dietary summaries used participant-level mean intakes from three recalls.

All 39 outcome analyses were exploratory. Separate linear regression models represented ordering frequency as four categories, with <1/month or no use as the reference. Age, sex, and education were included to address sociodemographic differences between groups. Full models additionally included physical activity, household income, and total energy intake to assess associations conditional on these behavioral and socioeconomic characteristics and reported energy intake. Education was coded as bachelor's degree or higher versus lower education, and income as >30,000 versus ≤30,000 THB/month to limit model parameters. Age and energy intake were continuous. Physical activity was entered as ln(1 + total MET-min/week) to accommodate zero values and its skewed distribution. Energy intake was omitted when energy was the outcome.

Natural-log models estimated relative differences in body fat mass, visceral and subcutaneous fat areas, visceral-to-subcutaneous fat ratio, fasting insulin, HOMA-IR, total sugars intake, and dietary fiber intake. Other outcomes used their original scales. HC3 robust standard errors were used [22]. Joint Wald F tests evaluated the three ordering-frequency coefficients. Benjamini–Hochberg adjustment across all 39 overall tests controlled the false discovery rate (FDR) at $q < 0.05$ [23].

Category contrasts were presented with pointwise 95% confidence intervals based on the Student t distribution and residual degrees of freedom. Log-scale coefficients and confidence limits were converted to percentage differences in modeled geometric means using $100 \times [\exp(\text{coefficient}) - 1]$. Other contrasts are absolute differences, with body fat percentage expressed in percentage points. Category contrasts were interpreted descriptively because their confidence intervals were not multiplicity-adjusted. The main inference concerned overall categorical associations.

Complete-observation analyses included 94 participants for 35 outcomes and 93 participants for waist circumference, hip circumference, waist-to-hip ratio, and waist-to-height ratio. No missing values were imputed. Additional analyses performed during revision assessed model sensitivity using reduced models adjusted for age, sex, and education and leave-one-out analyses, with FDR adjustment repeated for each analysis set. Leave-one-out analyses also assessed changes in the magnitude and direction of category-specific estimates after omitting each complete observation in turn. The resulting ranges were expressed on the same effect scales as the full-sample contrasts and represent sensitivity summaries rather than confidence

intervals. Covariate distributions across frequency categories and model diagnostics were also examined. Detailed procedures are provided in the Supplementary Methods.

3. Results

3.1. Food Ordering Application Use and Participant Characteristics

Among the 94 participants, 39 (41.5%) reported ordering food or beverages through applications at least once per month, while 55 (58.5%) reported ordering less than once per month or no use. Among the 39 participants ordering at least monthly, 7 (17.9%) reported ordering once per month, 19 (48.7%) reported ordering 2–3 times per month, and 13 (33.3%) reported ordering 2–3 times per week. The primary application type was a food delivery platform for 20 participants (51.3%) and a convenience store or supermarket application for 19 (48.7%). Desserts or sweets were the most commonly reported ordering category (22 participants, 56.4%), followed by beverages (17 participants, 43.6%). Participants could select up to three food and beverage categories (Table 1).

Table 1. Food ordering application use, ordering patterns, and preferences.

Question/Response	*n* (%)
Reported ordering frequency ($N = 94$)	
<1/month or no use	55 (58.5%)
1/month	7 (7.4%)
2–3/month	19 (20.2%)
2–3/week	13 (13.8%)
4–6/week	0 (0.0%)
Daily	0 (0.0%)
Primary application type (≥1/month group, $n = 39$)	
Food delivery platform	20 (51.3%)
Convenience store/supermarket app	19 (48.7%)
Restaurant app	0 (0.0%)
Usual ordering times	
Breakfast	17 (43.6%)
Lunch	12 (30.8%)
Afternoon snack	14 (35.9%)
Dinner	12 (30.8%)
Before bedtime	12 (30.8%)
Commonly ordered food and beverage categories	
Single-dish meals	12 (30.8%)
Fried/high-fat foods	1 (2.6%)
Noodle dishes	7 (17.9%)
Fast food	10 (25.6%)
Desserts/sweets	22 (56.4%)
Beverages	17 (43.6%)
Health-oriented foods	2 (5.1%)
Other	5 (12.8%)
Restaurant selection criteria	
Affordable food prices	21 (53.8%)
Short delivery time	16 (41.0%)
Free/low delivery fee	12 (30.8%)
Good reviews/ratings	7 (17.9%)
Appealing food photos	9 (23.1%)
Previously used restaurant	11 (28.2%)
Preferred/specific menu	3 (7.7%)
Healthy menu	8 (20.5%)
Restaurant-specific promotions	14 (35.9%)
Other	0 (0.0%)

Table 1. *Cont.*

Question/Response	*n* (%)
Reasons for using the application	
Convenience	17 (43.6%)
Limited time to cook/shop	12 (30.8%)
Promotions/discounts	18 (46.2%)
Affordable delivery fee	14 (35.9%)
Wide restaurant selection	13 (33.3%)
Ease of use	5 (12.8%)
Habit	4 (10.3%)
Reduce time spent outside the home	0 (0.0%)
Other	0 (0.0%)

Data are presented as n (%). Percentages for reported ordering frequency were calculated among all participants ($N = 94$). All other percentages were calculated among participants reporting application-based ordering at least once per month ($n = 39$). The reference group comprised participants reporting ordering less than once per month, including no use ($n = 55$). The interview referred to the month preceding data collection. Primary application type represents the single category used most frequently; participants could also have used other application types. Multiple responses were permitted for ordering times. Participants could select up to three responses for food and beverage categories, restaurant-selection criteria, and reasons for application use; percentages within these sections may therefore exceed 100%.

Table 2 summarizes participant characteristics according to food-ordering application use frequency. Participants reporting ordering at least once per month were younger than those reporting less frequent ordering or no use (median age, 42.0 versus 48.0 years; $p < 0.001$) and were more often female (82.1% versus 43.6%; $p < 0.001$). Educational attainment differed between groups ($p = 0.004$). Median moderate-intensity physical activity was higher in the ≥1/month group (360 versus 0 MET-min/week; $p = 0.009$), whereas total physical activity did not differ significantly (1191 versus 840 MET-min/week; $p = 0.218$). No statistically significant between-group differences were observed in alcohol consumption, smoking status, marital status, household income, self-reported underlying conditions, vigorous-intensity activity, or walking (all $p > 0.05$).

Table 2. Participant characteristics according to food ordering application use.

Characteristic	≥1/Month ($n = 39$)	<1/Month or No Use ($n = 55$)	*p* Value
Age (years)	42.00 (34.50–48.00)	48.00 (44.00–53.00)	<0.001
Sex			<0.001
Male	7 (17.9%)	31 (56.4%)	
Female	32 (82.1%)	24 (43.6%)	
Alcohol drinking in past 12 months			0.341
Yes	24 (61.5%)	39 (70.9%)	
No	15 (38.5%)	16 (29.1%)	
Smoking status			0.237
Current	3 (7.7%)	8 (14.5%)	
Former	2 (5.1%)	7 (12.7%)	
Never	34 (87.2%)	40 (72.7%)	
Education			0.004
Primary school	0 (0.0%)	10 (18.2%)	
Lower secondary/vocational	6 (15.4%)	10 (18.2%)	
Upper secondary/vocational	6 (15.4%)	14 (25.5%)	
Bachelor's degree	20 (51.3%)	11 (20.0%)	
Master's degree	7 (17.9%)	10 (18.2%)	

Table 2. *Cont.*

Characteristic	≥1/Month (n = 39)	<1/Month or No Use (n = 55)	p Value
Marital status			0.193
Single	15 (38.5%)	13 (23.6%)	
Married	21 (53.8%)	32 (58.2%)	
Divorced	3 (7.7%)	6 (10.9%)	
Widowed	0 (0.0%)	4 (7.3%)	
Monthly household income (THB)			0.599
<5000	0 (0.0%)	1 (1.8%)	
5001–10,000	1 (2.6%)	3 (5.5%)	
10,001–15,000	6 (15.4%)	6 (10.9%)	
15,001–20,000	6 (15.4%)	5 (9.1%)	
20,001–25,000	2 (5.1%)	9 (16.4%)	
25,001–30,000	3 (7.7%)	4 (7.3%)	
>30,000	21 (53.8%)	27 (49.1%)	
Self-reported underlying condition			0.910
None	24 (61.5%)	34 (61.8%)	
Hypertension	7 (17.9%)	8 (14.5%)	
Diabetes mellitus	2 (5.1%)	3 (5.5%)	
Dyslipidemia	1 (2.6%)	4 (7.3%)	
Other diseases	5 (12.8%)	6 (10.9%)	
Physical activity			
Total physical activity (MET-min/week)	1191.00 (468.50–2695.50)	840.00 (115.50–1953.00)	0.218
Vigorous activity (MET-min/week)	0.00 (0.00–840.00)	0.00 (0.00–1152.00)	0.911
Moderate activity (MET-min/week)	360.00 (0.00–840.00)	0.00 (0.00–360.00)	0.009
Walking (MET-min/week)	231.00 (0.00–371.25)	132.00 (0.00–453.75)	0.447

Data are presented as median (Q1–Q3) or n (%). Continuous variables were compared using two-sided Mann–Whitney U tests. Categorical variables were compared using Pearson's chi-square test or conditional Monte Carlo Pearson chi-square tests for sparse tables. Physical activity scores followed the IPAQ short-form protocol. MET, metabolic equivalent of task.

3.2. Anthropometric Measures, Blood Pressure, and Body Composition According to Food-Ordering Application Use Frequency

Table 3 summarizes anthropometric measures, blood pressure, and body composition according to food-ordering application use frequency. In unadjusted comparisons, participants reporting ordering at least once per month had higher BMI (28.39 ± 6.19 versus 24.08 ± 3.16 kg/m^2; $p < 0.001$) and body fat percentage (40.60 ± 6.44% versus 32.00 ± 6.25%; $p < 0.001$) than those reporting less frequent ordering or no use. Median device-estimated visceral and subcutaneous fat areas were also higher in the ≥1/month group (104.20 versus 81.50 cm^2, $p = 0.003$; and 270.70 versus 156.40 cm^2, $p < 0.001$, respectively), whereas the visceral-to-subcutaneous fat ratio was lower (0.39 versus 0.53; $p < 0.001$). Systolic and diastolic blood pressure did not differ significantly between groups (both $p > 0.05$).

Table 3. Anthropometric measures, blood pressure, and body composition according to food-ordering application use frequency.

Measure	≥1/Month (n = 39)	<1/Month or No Use (n = 55)	p Value
Height (cm)	157.40 (154.60–163.75)	160.30 (155.00–166.25)	0.274
Weight (kg)	72.88 ± 18.55	62.82 ± 11.32	0.004
BMI (kg/m^2)	28.39 ± 6.19	24.08 ± 3.16	<0.001
Waist circumference (cm)	88.09 ± 15.23	81.08 ± 9.06	0.013
Hip circumference (cm)	103.50 ± 12.59	93.47 ± 5.90	<0.001
Waist-to-hip ratio	0.85 ± 0.07	0.87 ± 0.07	0.199
Systolic BP (mmHg)	132.97 ± 18.98	135.65 ± 17.39	0.487
Diastolic BP (mmHg)	89.51 ± 13.03	88.11 ± 10.86	0.584

Table 3. *Cont.*

Measure	≥1/Month (n = 39)	<1/Month or No Use (n = 55)	p Value
Heart rate (bpm)	83.38 ± 9.25	75.44 ± 10.35	<0.001
Skeletal muscle mass (kg)	20.60 (18.65–26.65)	24.10 (18.00–28.65)	0.747
Body fat mass (kg)	28.90 (23.05–36.05)	19.60 (16.15–22.25)	<0.001
Body fat (%)	40.60 ± 6.44	32.00 ± 6.25	<0.001
Visceral fat area (cm^2)	104.20 (79.70–131.75)	81.50 (73.10–99.70)	0.003
Subcutaneous fat area (cm^2)	270.70 (211.60–335.55)	156.40 (129.90–190.30)	<0.001
Visceral-to-subcutaneous fat ratio	0.39 (0.34–0.43)	0.53 (0.44–0.63)	<0.001
Abdominal fat ratio	0.85 ± 0.06	0.85 ± 0.05	0.821
Waist-to-height ratio	0.55 ± 0.09	0.50 ± 0.05	0.003
Muscle mass (kg)	37.00 (33.30–43.30)	41.10 (33.15–48.15)	0.797
Body cell mass (kg)	25.50 (22.80–29.85)	28.30 (22.60–33.20)	0.848
Total body water (L)	29.10 (26.05–33.65)	32.10 (25.90–37.55)	0.788

Data are presented as mean ± SD or median (Q1–Q3). Between-group comparisons used two-sided Welch's t tests for variables summarized as mean ± SD and two-sided Mann–Whitney U tests for variables summarized as median (Q1–Q3). Waist circumference, hip circumference, waist-to-hip ratio, and waist-to-height ratio were available for 93 participants: 39 in the ≥1/month group and 54 in the <1/month or no-use group. All other measures were available for 94 participants: 39 and 55, respectively. Body composition measures were estimated using bioelectrical impedance analysis. The p values are unadjusted for covariates and multiple comparisons. BMI, body mass index; BP, blood pressure; SD, standard deviation; Q1–Q3, first–third quartiles.

3.3. Biochemical Measures and HOMA-IR

Table 4 summarizes biochemical measures and HOMA-IR according to food-ordering application use frequency. In unadjusted comparisons, participants reporting ordering at least once per month had higher median fasting insulin concentrations (9.20 versus 5.10 μIU/mL; $p < 0.001$) and HOMA-IR values (2.23 versus 1.24; $p < 0.001$) than those reporting less frequent ordering or no use. No statistically significant between-group differences were observed in fasting blood glucose, total cholesterol, triglycerides, HDL cholesterol, or LDL cholesterol (all $p > 0.05$).

Table 4. Biochemical measures and HOMA-IR according to food-ordering application use frequency.

Measure	≥1/Month (n = 39)	<1/Month or No Use (n = 55)	p Value
Fasting blood glucose (mg/dL)	99.00 (91.50–103.50)	98.00 (90.00–105.00)	0.744
Total cholesterol (mg/dL)	203.00 (162.00–224.50)	203.00 (182.50–228.00)	0.475
Triglycerides (mg/dL)	124.00 (84.50–162.00)	114.00 (82.50–159.50)	0.487
HDL cholesterol (mg/dL)	61.31 ± 10.00	61.38 ± 14.54	0.977
LDL cholesterol (mg/dL)	124.15 ± 36.09	130.20 ± 48.92	0.492
Fasting insulin (μIU/mL)	9.20 (6.90–15.30)	5.10 (3.70–8.70)	<0.001
HOMA-IR	2.23 (1.63–4.20)	1.24 (0.86–2.19)	<0.001

Data are presented as mean ± SD or median (Q1–Q3). All measures were available for 94 participants: 39 in the ≥1/month group and 55 in the <1/month or no-use group. Between-group comparisons used two-sided Welch's t tests for variables summarized as mean ± SD and two-sided Mann–Whitney U tests for variables summarized as median (Q1–Q3). The p values are unadjusted for covariates and multiple comparisons. HOMA-IR is an indirect index of insulin resistance. HDL, high-density lipoprotein; LDL, low-density lipoprotein; HOMA-IR, homeostatic model assessment of insulin resistance; SD, standard deviation; Q1–Q3, first–third quartiles.

3.4. Dietary Intake Based on Three 24-h Recalls

Figures 2 and 3 summarize dietary intake estimated from three 24-h recalls. In unadjusted comparisons, the percentages of energy derived from carbohydrate, protein, and fat did not differ significantly between participants reporting ordering at least once per month and those reporting less frequent ordering or no use (all $p > 0.05$; Figure 2). Daily energy intake also did not differ significantly between groups (medians, 1750.32 versus 1881.89 kcal/day; $p = 0.509$). The ≥1/month group had higher total sugars intake (median

[Q1–Q3], 47.69 [27.94–72.69] versus 21.27 [12.77–38.92] g/day; $p < 0.001$) and lower dietary fiber intake (9.48 [5.10–15.95] versus 14.66 [7.71–20.20] g/day; $p = 0.009$). Daily intakes of carbohydrate, protein, fat, saturated fat, cholesterol, and sodium did not differ significantly between groups (all $p > 0.05$; Figure 3).

3.5. Associations Between Food Ordering Application Use Frequency and Selected Outcomes

The four ordering-frequency categories comprised 55 participants reporting <1/month or no use, seven reporting 1/month, 19 reporting 2–3/month, and 13 reporting 2–3/week. Table 5 presents unadjusted outcome summaries alongside adjusted overall tests. Median total sugars intake across these categories was 21.27, 37.62, 58.33, and 31.76 g/day, respectively; corresponding median dietary fiber intake was 14.66, 7.12, 15.55, and 7.18 g/day.

Table 5. Unadjusted outcome summaries and adjusted overall associations across food-ordering application use frequency categories.

Outcome	<1/Month or No Use ($n = 55$)	1/Month ($n = 7$)	2–3/Month ($n = 19$)	2–3/Week ($n = 13$)	Adjusted Overall p	FDR q
BMI (kg/m^2)	24.01 (22.32–25.69)	23.95 (22.07–27.56)	29.26 (27.18–30.81)	25.75 (24.32–35.32)	<0.001	<0.001
Body fat mass (kg)	19.60 (16.15–22.25)	22.10 (20.65–26.40)	31.20 (25.10–34.55)	24.30 (23.10–43.00)	<0.001	<0.001
Body fat (%)	32.90 (27.00–36.60)	36.80 (35.00–38.55)	43.10 (36.85–45.20)	41.00 (38.70–45.70)	<0.001	<0.001
Visceral fat area (cm^2)	81.50 (73.10–99.70)	78.20 (70.45–104.25)	109.40 (94.05–122.30)	97.80 (76.10–145.20)	<0.001	<0.001
Subcutaneous fat area (cm^2)	156.40 (129.90–190.30)	197.70 (186.95–248.60)	292.60 (225.75–332.20)	218.70 (212.90–427.60)	<0.001	<0.001
Visceral-to-subcutaneous fat ratio	0.53 (0.44–0.63)	0.40 (0.34–0.45)	0.40 (0.35–0.42)	0.37 (0.34–0.42)	0.030	0.061
Waist-to-height ratio	0.51 (0.47–0.53)	0.50 (0.46–0.55)	0.55 (0.53–0.60)	0.53 (0.50–0.66)	<0.001	0.002
Fasting insulin (µIU/mL)	5.10 (3.70–8.70)	6.50 (5.45–8.50)	9.40 (8.35–15.30)	10.00 (7.80–21.30)	<0.001	<0.001
HOMA-IR	1.24 (0.86–2.19)	1.52 (1.22–1.99)	3.17 (1.89–4.20)	2.54 (1.79–5.36)	<0.001	<0.001
Total sugars intake (g/day)	21.27 (12.77–38.92)	37.62 (28.28–48.53)	58.33 (41.41–74.76)	31.76 (21.76–51.42)	<0.001	<0.001
Dietary fiber intake (g/day)	14.66 (7.71–20.20)	7.12 (5.60–8.84)	15.55 (8.60–17.78)	7.18 (4.36–10.31)	0.003	0.007

Values are unadjusted medians (Q1–Q3); dietary values represent participant-level three-day mean intakes. Adjusted overall p values are from joint Wald F tests with HC3 robust standard errors, adjusting for age, sex, education, ln(1 + total physical activity), household income, and total energy intake. FDR q values were calculated using the Benjamini–Hochberg procedure across all 39 outcomes. Overall tests assess differences across frequency categories, not individual pairwise contrasts. Waist-to-height ratio analyses included 93 participants, with 54 in the <1/month or no-use category. All other displayed outcomes included 94 participants. BMI, body mass index; HOMA-IR, homeostatic model assessment of insulin resistance; FDR, false discovery rate; Q1–Q3, first–third quartiles.

After adjustment for age, sex, education, physical activity, household income, and total energy intake, overall associations met the FDR threshold for 10 of the 11 displayed outcomes: BMI, body fat mass, body fat percentage, visceral fat area, subcutaneous fat area, waist-to-height ratio, fasting insulin, HOMA-IR, total sugars intake, and dietary fiber intake (all $q < 0.05$). The visceral-to-subcutaneous fat ratio did not meet this threshold (overall

$p = 0.030$; $q = 0.061$). FDR adjustment included all 39 outcomes, with the complete results presented in Supplementary Table S1.

Table 6 presents adjusted category-specific contrasts relative to the <1/month or no-use category, with pointwise 95% confidence intervals. These contrasts were not adjusted for multiple comparisons and are reported descriptively.

Table 6. Adjusted contrasts and pointwise 95% confidence intervals by food-ordering application ordering frequency.

Outcome	1/Month vs. Reference	2–3/Month vs. Reference	2–3/Week vs. Reference
BMI (kg/m^2)	+2.834 (−0.380 to +6.048)	+5.387 (+3.105 to +7.670)	+6.383 (+2.710 to +10.056)
Body fat mass (kg)	+30.6% (+6.7 to +59.9%)	+53.1% (+30.7 to +79.3%)	+51.7% (+16.7 to +97.1%)
Body fat (percentage points)	+3.504 (−0.089 to +7.098)	+7.229 (+4.408 to +10.050)	+6.385 (+1.910 to +10.860)
Visceral fat area (cm^2)	+27.8% (+6.2 to +53.8%)	+48.6% (+28.6 to +71.7%)	+53.3% (+17.5 to +100.2%)
Subcutaneous fat area (cm^2)	+39.6% (+4.9 to +85.9%)	+64.9% (+37.1 to +98.3%)	+57.7% (+14.1 to +117.9%)
Visceral-to-subcutaneous fat ratio	−8.5% (−18.7 to +3.0%)	−9.9% (−16.4 to −2.9%)	−2.7% (−11.8 to +7.2%)
Waist-to-height ratio	+0.040 (−0.011 to +0.091)	+0.068 (+0.033 to +0.103)	+0.084 (+0.030 to +0.139)
Fasting insulin (µIU/mL)	+59.6% (−9.6 to +181.7%)	+129.0% (+53.7 to +241.4%)	+139.1% (+41.2 to +304.8%)
HOMA-IR	+58.2% (−14.3 to +192.0%)	+147.6% (+67.0 to +267.2%)	+167.9% (+42.9 to +402.5%)
Total sugars intake (g/day)	+146.7% (+4.7 to +481.1%)	+242.8% (+123.1 to +426.6%)	+139.6% (+32.6 to +332.8%)
Dietary fiber intake (g/day)	−47.0% (−64.6 to −20.8%)	−12.2% (−35.6 to +19.6%)	−47.3% (−66.1 to −18.2%)

Values are adjusted contrasts with pointwise 95% confidence intervals relative to the <1/month or no-use category. Models used the covariates specified in Table 5. BMI contrasts are absolute differences in kg/m^2, waist-to-height ratio contrasts are absolute differences in the ratio, and body fat percentage contrasts are percentage-point differences. For all other displayed outcomes, contrasts are relative percentage differences in modeled geometric means, calculated as $100 \times [\exp(\beta) - 1]$. Analyses included 93 participants for waist-to-height ratio and 94 for all other displayed outcomes. The 33 contrasts were not adjusted for multiple comparisons and are interpreted descriptively. Overall FDR q values do not apply to individual contrasts. BMI, body mass index; HOMA-IR, homeostatic model assessment of insulin resistance; FDR, false discovery rate.

The same 10 displayed outcomes retained $q < 0.05$ in the reduced models and all leave-one-out analyses. For the visceral-to-subcutaneous fat ratio, q was 0.023 in the reduced model and ranged from 0.016 to 0.131 across leave-one-out analyses (Table S2). Covariate distributions across frequency categories are presented in Table S3; the 1/month and 2–3/week categories each included one male participant. Outcome-specific sample sizes and regression diagnostics are presented in Table S4.

None of the 33 category-specific contrasts displayed in Table 6 changed direction in leave-one-out analyses, although their magnitudes varied (Table S5). For example, the once-monthly BMI contrast ranged from 2.14 to 3.84 kg/m^2, compared with 2.83 kg/m^2 in the full sample. The corresponding total sugars contrast ranged from 112.2% to 238.4%, compared with 146.7% in the full sample. These minimum–maximum ranges summarize leave-one-out estimates and are not confidence intervals.

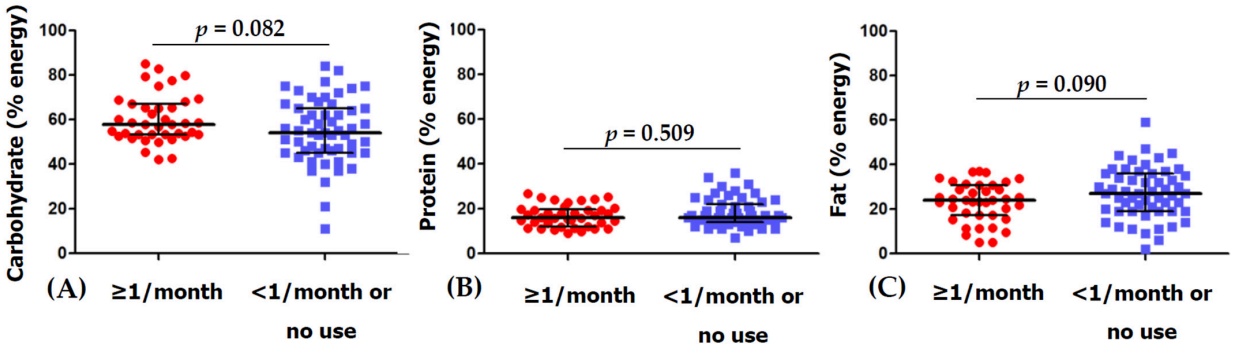


Figure 2. Percentage of energy derived from macronutrients according to food-ordering application use frequency. (**A**) Carbohydrate; (**B**) protein; and (**C**) fat. Each point represents one participant's three-day mean percentage of energy derived from the indicated macronutrient, based on three 24-h dietary recalls. Red circles represent the ≥1/month group (n = 39), and blue squares represent the <1/month or no-use group (n = 55). Horizontal lines indicate medians, and error bars indicate the first and third quartiles (Q1–Q3). Between-group comparisons used two-sided Mann–Whitney U tests. The *p* values are unadjusted for covariates and multiple comparisons.

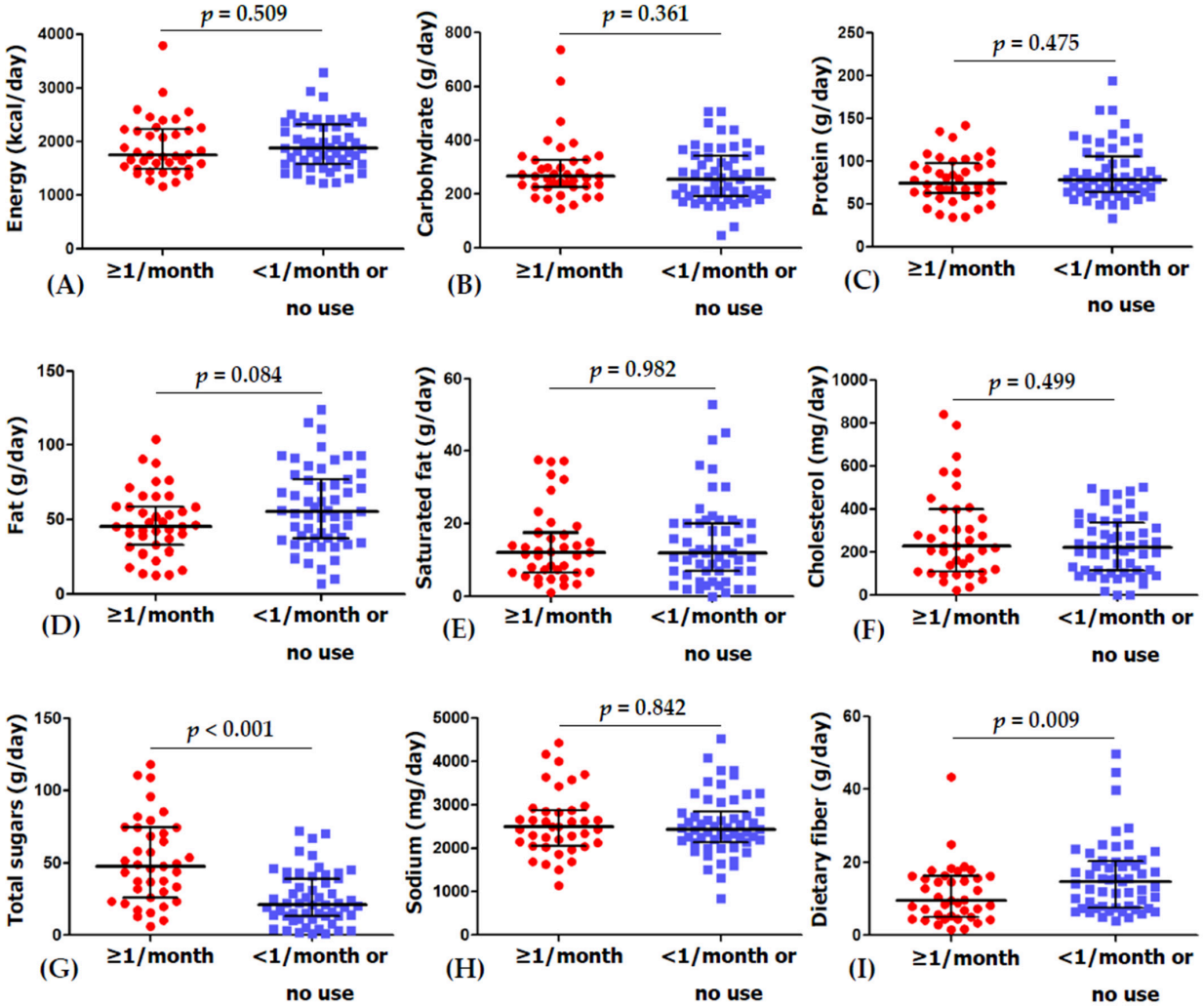


Figure 3. Three-day mean daily energy and nutrient intakes according to food-ordering application use frequency. (**A**) Energy; (**B**) carbohydrate; (**C**) protein; (**D**) fat; (**E**) saturated fat; (**F**) cholesterol; (**G**) total sugars; (**H**) sodium; and (**I**) dietary fiber. Each point represents one participant's mean daily intake across three 24-h dietary recalls. Red circles represent the ≥1/month group (n = 39), and blue squares represent the <1/month or no-use group (n = 55). Horizontal lines indicate medians, and

error bars indicate the first and third quartiles (Q1–Q3). Between-group comparisons used two-sided Mann–Whitney U tests. The *p* values are unadjusted for covariates and multiple comparisons. Dietary estimates represent intake from all reported foods and beverages and were not linked to specific application-based orders.

4. Discussion

This exploratory cross-sectional study found differences in dietary intake, adiposity, and insulin-related markers according to food-ordering application use at a local government workplace in Chiang Mai. Participants reporting ordering at least monthly had higher total sugars intake, lower dietary fiber intake, greater adiposity, and higher fasting insulin and HOMA-IR than those reporting less frequent ordering or no use. Overall associations across ordering-frequency categories were also observed after adjustment for measured covariates and correction for multiple outcome testing. These findings extend the description of application use beyond weight status by examining dietary intake and measured cardiometabolic markers in the same participants.

The ordering preferences in Table 1 help contextualize the dietary findings. Among participants ordering at least monthly, desserts or sweets were the most frequently selected food category (56.4%), followed by beverages (43.6%). Promotions or discounts (46.2%) and convenience (43.6%) were commonly reported motivations. Laboratory analysis of popular delivery items in Bangkok identified substantial sugar content in several desserts and non-alcoholic beverages [4], while Malaysian workers commonly ordered coffee and sugar-sweetened beverages with meals [10]. Wang et al. also documented the prominence of discretionary menu items and their marketing attributes on an Australian delivery platform [24]. Together, these observations support considering food preferences alongside convenience and price-related motivations when studying application-based purchasing. The Table 1 percentages describe respondents selecting each category, rather than the proportions of orders, and the beverage category included drinks without distinguishing their sugar content.

The demographic profile also places the findings in context. Participants ordering at least monthly were younger and more often women, and educational attainment differed between groups. Younger age was associated with service use in both a five-country survey and a Malaysian workplace study [10,25]. The predominance of women in the present group differs from the higher odds of use among men in the five-country survey [25], illustrating variation across settings. Moderate-intensity activity was higher in the group ordering at least monthly, whereas total activity did not differ significantly. These differences informed covariate adjustment and indicate that application use should be considered alongside the characteristics and routines of its users.

Unadjusted comparisons showed higher BMI, waist circumference, waist-to-height ratio, body fat mass and percentage, and estimated visceral and subcutaneous fat areas in the group ordering at least monthly. A UK study similarly reported an association between takeaway delivery application use and obesity [9], although frequent service use was not associated with overweight or obesity among Malaysian workers [10]. The present findings add measurements of dietary composition and fat distribution to this mixed evidence. The related adiposity measures describe overlapping aspects of body composition; BMI and waist-related measures provide anthropometric context for the device-derived fat estimates.

The fat-compartment findings are relevant to previous evidence on abdominal adiposity. In the Framingham Heart Study, both visceral and subcutaneous adipose tissue were associated with insulin resistance, with a stronger association for visceral adipose tissue [26]. Research has also identified different cardiometabolic associations for adipose depots after accounting for BMI [27]. Here, both estimated fat areas were higher in the group ordering at least monthly, while their ratio was lower in the unadjusted comparison.

The ratio therefore describes relative fat distribution and should be considered alongside the individual compartments. Its overall association did not meet the FDR threshold in the full model ($q = 0.061$; Table 5), and its q value varied across reduced and leave-one-out analyses (Table S2).

Fasting insulin and HOMA-IR were higher in the group ordering at least monthly, while fasting glucose and measured lipid concentrations did not differ significantly. Physiological studies have established the relationship between insulin sensitivity and insulin secretion [28]. HOMA-IR provides an indirect fasting index based on glucose and insulin [18], allowing characterization of an aspect of glucose–insulin regulation beyond fasting glucose alone. Because insulin contributes directly to its calculation, the two findings are related and should be interpreted together rather than as independent evidence or as a clinical diagnosis of insulin resistance.

Dietary composition was a prominent difference between groups: median total sugars intake was 47.69 versus 21.27 g/day, while median fiber intake was 9.48 versus 14.66 g/day. Evidence from other settings supports studying these dietary dimensions in relation to metabolic health. A UK Biobank analysis associated sugar-sweetened beverage intake with visceral adipose tissue mass [29]. Trials involving defined sweetened beverages reported increased hepatic de novo lipogenesis [30] and changes in visceral adiposity or insulin sensitivity [15,31]. For fiber, an observational study of US adults reported an association with HOMA-based insulin resistance [32], and an isoenergetic intervention found higher insulin sensitivity after six weeks of a high-cereal-fiber diet than after a high-protein diet [33]. These studies provide biological context for the dietary findings, although their specific sugar sources and dietary interventions differ from the total sugars and fiber estimates assessed here.

Reported energy intake and macronutrient energy distribution did not differ significantly between groups. Energy totals and macronutrient percentages summarize broad aspects of diet, whereas total sugars and fiber provide additional information about the composition of carbohydrate-containing foods. Short-term dietary reports and accumulated adiposity also represent different time periods. The OPEN study documented dietary reporting errors and their relationship with BMI [34], offering a further explanation for differences between reported intake and body composition. The results therefore highlight dietary composition without demonstrating equivalent energy intake or independence from long-term energy balance.

The categorical frequency analysis identified overall associations without a consistently graded pattern. Median total sugars intake was highest in the 2–3/month category, while median fiber intake was higher in that category than in either the 1/month or 2–3/week category (Table 5). Frequency alone does not specify portion sizes, the number of people served, or the nutritional composition of purchases. Variation in these characteristics and in application types, together with sampling variability in small groups, could contribute to the pattern. The unequally spaced categories were modeled categorically, and the results do not establish a dose–response relationship. Overall inference used FDR-adjusted tests; the contrasts and pointwise confidence intervals in Table 6 describe individual differences without adjustment for multiple contrasts.

Sensitivity analyses added during revision provided further information on the adjusted findings. The 10 displayed outcomes meeting $q < 0.05$ in the full models retained this threshold in reduced models and all leave-one-out analyses (Table S2). The visceral-to-subcutaneous fat ratio was less consistent, with $q = 0.023$ in the reduced model and leave-one-out q values of 0.016–0.131. Although none of the 33 displayed category-specific contrasts changed direction, their magnitudes varied after individual observations were omitted, particularly in the once-monthly category (Table S5). These findings support

consistency in the direction of the displayed estimates under the examined omissions, while indicating that their magnitudes remain sensitive to individual observations. Stability of statistical significance should therefore not be equated with precise estimation.

The concurrent assessment of diet, anthropometry, body composition, and fasting biochemical markers is a strength of this study. Reporting all 39 overall tests and the additional sensitivity analyses also make the scope of the exploratory analyses transparent. Several limitations nevertheless qualify the interpretation of the findings. First, the cross-sectional design cannot establish temporal order. Pre-existing adiposity, dietary habits, or reliance on convenience foods could influence application use, and ordering during the preceding month may not represent the longer-term exposures reflected in metabolic measures. Voluntary recruitment for health assessments at one workplace may also select participants with different health awareness or concerns from non-participants, limiting generalizability to other workplaces and the wider working-age population.

Second, the original sample size calculation concerned the broader survey rather than application-use comparisons or multivariable analyses, and its assumed precision does not apply directly to this volunteer sample. Small frequency groups and limited covariate overlap may reduce the precision and stability of category-specific estimates; the 1/month and 2–3/week groups each included only one man (Table S3). These exploratory contrasts therefore require cautious interpretation, particularly where confidence intervals are wide. Residual departures from normality and potentially influential observations are documented in Table S4 and were examined through the sensitivity analyses described above. Residual confounding remains possible because habitual eating-out frequency, sugar-sweetened beverage consumption, and overall dietary quality were not sufficiently characterized.

Third, the exposure combined delivery and convenience-store or supermarket applications to capture a broad mode of obtaining food and beverages. These services can represent different purchasing behaviors: the UK study found different obesity associations for takeaway delivery applications and online grocery services [9]. Only the most frequently used type was recorded, and participants could use several types, so the pooled findings cannot identify platform-specific associations or be interpreted as a measure of unhealthy purchasing. The reference group combined less-than-monthly ordering with no use. Three consecutive 24-h recalls also provide limited information on usual intake and within-person variation [35,36]. Total sugars were not separated into naturally occurring, added, or free sugars, and recalled foods were not linked to application orders. These data therefore cannot attribute the dietary differences to specific purchases or establish dietary mediation. Nonsignificant glucose and lipid comparisons should not be interpreted as equivalence [37].

Finally, BIA provides device-derived body composition estimates rather than direct imaging measurements. A comparison of multifrequency BIA with computed tomography in Korean adults found discrepancies that varied with age, sex, and BMI [38]. This evidence concerns a different analyzer; the Mediana i55 was not validated against imaging within the present study. The fat-area estimates should therefore be interpreted with this measurement limitation in mind. The observed dietary and metabolic associations provide a basis for longitudinal studies linking detailed purchasing records with repeated dietary assessments and validated body composition and metabolic measurements.

5. Conclusions

Among adults at a local government workplace in Chiang Mai, participants reporting food-ordering application use at least monthly had higher reported total sugars intake, lower dietary fiber intake, greater adiposity, and higher fasting insulin and HOMA-IR than those reporting less frequent use or no use. Overall associations across ordering-

frequency categories were also observed after covariate adjustment and correction for multiple outcome testing. These exploratory findings link food-ordering behaviors with dietary composition and cardiometabolic markers in this workplace sample. Larger, more representative longitudinal studies incorporating detailed purchasing records would help confirm these associations and clarify their temporal relationships.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/nu18234005/s1, Supplementary Methods: Statistical implementation; Supplementary Results: Model diagnostics and sensitivity analyses; Table S1: Overall adjusted associations across food-ordering application use frequency categories for all 39 outcomes; Table S2: Sensitivity of the highlighted associations; Table S3: Covariate distributions across ordering frequency categories; Table S4: Sample sizes and regression diagnostics for all 39 full models; Table S5: Full-sample adjusted contrasts and leave-one-out ranges for the outcomes displayed in Table 6.

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Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Abbreviations

The following abbreviations are used in this manuscript:

BMI	Body mass index
HDL-C	High-density lipoprotein cholesterol
HOMA-IR	Homeostatic model assessment of insulin resistance
LDL-C	Low-density lipoprotein cholesterol
IPAQ-SF	International physical activity questionnaire–short form
SD	Standard deviation
HC3	Heteroskedasticity-consistent standard error estimator, type 3
FDR	False discovery rate
MET	Metabolic equivalent of task
BIA	Bioelectrical impedance analysis

References

1. Burlea-Schiopoiu, A.; Puiu, S.; Dinu, A. The impact of food delivery applications on Romanian consumers' behaviour during the COVID-19 pandemic. *Socioecon. Plan. Sci.* **2022**, *82*, 101220. [CrossRef] [PubMed]
2. Tan, S.Y.; Lim, S.Y.; Yeo, S.F. Online food delivery services: Cross-sectional study of consumers' attitude in Malaysia during and after the COVID-19 pandemic. *F1000Research* **2026**, *10*, 972. [CrossRef] [PubMed]
3. Dsouza, D.; Sharma, D. Online food delivery portals during COVID-19 times: An analysis of changing consumer behavior and expectations. *Int. J. Innov. Sci.* **2021**, *13*, 218–232. [CrossRef]
4. Jindarattanaporn, N.; Suya, I.; Lorenzetti, L.; Kantachuvesiri, S.; Thamarangsi, T. Nutritional content of popular menu items from online food delivery applications in Bangkok, Thailand: Are they healthy? *Int. J. Environ. Res. Public Health* **2023**, *20*, 3992. [CrossRef] [PubMed]
5. Chimphimon, S.; Chunjan, K.; Soonsan, N.; Kattiyapornpong, U.; Thongmun, S. Customers' perceived value influenced their decision to utilize mobile food delivery applications in Thailand. *J. Hosp. Tour. Insights* **2025**, *8*, 3240–3260. [CrossRef]
6. Inthong, C.; Champahom, T.; Jomnonkwao, S.; Chatpattananan, V.; Ratanavaraha, V. Exploring factors affecting consumer behavioral intentions toward online food ordering in Thailand. *Sustainability* **2022**, *14*, 8493. [CrossRef]
7. Dai, X.; Wu, L.; Hu, W. Nutritional quality and consumer health perception of online delivery food in the context of China. *BMC Public Health* **2022**, *22*, 2132. [CrossRef] [PubMed]
8. Chin, J.W.; Loh, W.M.L.; Ooi, Y.B.H.; Khor, B.H. Characteristics and nutrient profiles of foods and beverages on online food delivery systems. *Nutr. Bull.* **2025**, *50*, 250–261. [CrossRef] [PubMed]
9. Cummins, S.; Kalbus, A.I.; Cornelsen, L.; Adams, J.; Boyland, E.; Burgoine, T.; Law, C.; de Vocht, F.; White, M.; Yau, A. Social inequalities in the use of online food delivery services and associations with weight status: Cross-sectional analysis of survey and consumer data. *BMJ Public Health* **2024**, *2*, e000487. [CrossRef] [PubMed]
10. Chan, L.Y.; Moy, F.M. Online food delivery services usage and its associated factors among a work population in a middle income country, Malaysia. *J. Health Transl. Med.* **2025**, *28*, 24–33.
11. Jia, S.S.; Raeside, R.; Sainsbury, E.; Wardak, S.; Phongsavan, P.; Redfern, J.; Allman-Farinelli, M.; Fernandez, M.A.; Partridge, S.R.; Gibson, A.A. Use of online food retail platforms throughout the COVID-19 pandemic and associated diet-related chronic disease risk factors: A systematic review of emerging evidence. *Obes. Rev.* **2024**, *25*, e13720. [CrossRef] [PubMed]
12. Mozaffarian, D. Dietary and policy priorities for cardiovascular disease, diabetes, and obesity: A comprehensive review. *Circulation* **2016**, *133*, 187–225. [CrossRef] [PubMed]
13. Musaiger, A.O.; Al-Hazzaa, H.M. Prevalence and risk factors associated with nutrition-related noncommunicable diseases in the Eastern Mediterranean region. *Int. J. Gen. Med.* **2012**, *5*, 199–217. [CrossRef] [PubMed]
14. Whelton, P.K.; Appel, L.J.; Sacco, R.L.; Anderson, C.A.M.; Antman, E.M.; Campbell, N.; Dunbar, S.B.; Frohlich, E.D.; Hall, J.E.; Jessup, M.; et al. Sodium, blood pressure, and cardiovascular disease: Further evidence supporting the American Heart Association sodium reduction recommendations. *Circulation* **2012**, *126*, 2880–2889. [CrossRef] [PubMed]
15. Maersk, M.; Belza, A.; Stødkilde-Jørgensen, H.; Ringgaard, S.; Chabanova, E.; Thomsen, H.; Pedersen, S.B.; Astrup, A.; Richelsen, B. Sucrose-sweetened beverages increase fat storage in the liver, muscle, and visceral fat depot: A 6-mo randomized intervention study. *Am. J. Clin. Nutr.* **2012**, *95*, 283–289. [CrossRef] [PubMed]
16. Fox, C.S.; Massaro, J.M.; Hoffmann, U.; Pou, K.M.; Maurovich-Horvat, P.; Liu, C.-Y.; Vasan, R.S.; Murabito, J.M.; Meigs, J.B.; Cupples, L.A.; et al. Abdominal visceral and subcutaneous adipose tissue compartments: Association with metabolic risk factors in the Framingham Heart Study. *Circulation* **2007**, *116*, 39–48. [CrossRef] [PubMed]
17. Wildman, R.P.; Muntner, P.; Reynolds, K.; McGinn, A.P.; Rajpathak, S.; Wylie-Rosett, J.; Sowers, M.R. The obese without cardiometabolic risk factor clustering and the normal weight with cardiometabolic risk factor clustering: Prevalence and correlates of 2 phenotypes among the US population (NHANES 1999–2004). *Arch. Intern. Med.* **2008**, *168*, 1617–1624. [CrossRef] [PubMed]
18. Matthews, D.R.; Hosker, J.P.; Rudenski, A.S.; Naylor, B.A.; Treacher, D.F.; Turner, R.C. Homeostasis model assessment: Insulin resistance and β-cell function from fasting plasma glucose and insulin concentrations in man. *Diabetologia* **1985**, *28*, 412–419. [CrossRef] [PubMed]
19. Craig, C.L.; Marshall, A.L.; Sjöström, M.; Bauman, A.E.; Booth, M.L.; Ainsworth, B.E.; Pratt, M.; Ekelund, U.; Yngve, A.; Sallis, J.F.; et al. International physical activity questionnaire: 12-country reliability and validity. *Med. Sci. Sports Exerc.* **2003**, *35*, 1381–1395. [CrossRef] [PubMed]
20. Parklak, W.; Chuljerm, H.; Kawichai, S.; Fakfum, P.; Jiraya, P.; Kijkuokool, P.; Khiaolaongam, W.; Somnuk, S.; Kulprachakarn, K. Associations between nutrient intake and vascular inflammation among healthy adults living in rural and peri-urban particulate matter 2.5-affected areas: An exploratory study. *Nutrients* **2025**, *17*, 2867. [CrossRef] [PubMed]
21. Parklak, W.; Kulprachakarn, K.; Kawichai, S.; Fakfum, P.; Jiraya, P.; Kijkuokool, P.; Khiaolaongam, W.; Chuljerm, H. Association between dietary patterns and lifestyle habits with vascular inflammatory responses in individuals with hypertension living in PM2.5-polluted areas: A cross-sectional pilot study in Chiang Mai Province, Thailand. *Diseases* **2025**, *13*, 258. [CrossRef] [PubMed]

22. MacKinnon, J.G.; White, H. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *J. Econom.* **1985**, *29*, 305–325. [CrossRef]
23. Benjamini, Y.; Hochberg, Y. Controlling the false discovery rate: A practical and powerful approach to multiple testing. *J. R. Stat. Soc. Ser. B Methodol.* **1995**, *57*, 289–300. [CrossRef]
24. Wang, C.; Korai, A.; Jia, S.S.; Allman-Farinelli, M.; Chan, V.; Roy, R.; Raeside, R.; Phongsavan, P.; Redfern, J.; Gibson, A.A.; et al. Hunger for home delivery: Cross-sectional analysis of the nutritional quality of complete menus on an online food delivery platform in Australia. *Nutrients* **2021**, *13*, 905. [CrossRef] [PubMed]
25. Keeble, M.; Adams, J.; Sacks, G.; Vanderlee, L.; White, C.M.; Hammond, D.; Burgoine, T. Use of online food delivery services to order food prepared away-from-home and associated sociodemographic characteristics: A cross-sectional, multi-country analysis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5190. [CrossRef] [PubMed]
26. Preis, S.R.; Massaro, J.M.; Robins, S.J.; Hoffmann, U.; Vasan, R.S.; Irlbeck, T.; Meigs, J.B.; Sutherland, P.; D'Agostino, R.B., Sr.; O'Donnell, C.J.; et al. Abdominal subcutaneous and visceral adipose tissue and insulin resistance in the Framingham Heart Study. *Obesity* **2010**, *18*, 2191–2198. [CrossRef] [PubMed]
27. Agrawal, S.; Klarqvist, M.D.R.; Diamant, N.; Stanley, T.L.; Ellinor, P.T.; Mehta, N.N.; Philippakis, A.; Ng, K.; Claussnitzer, M.; Grinspoon, S.K.; et al. BMI-adjusted adipose tissue volumes exhibit depot-specific and divergent associations with cardiometabolic diseases. *Nat. Commun.* **2023**, *14*, 266. [CrossRef] [PubMed]
28. Kahn, S.E.; Prigeon, R.L.; McCulloch, D.K.; Boyko, E.J.; Bergman, R.N.; Schwartz, M.W.; Neifing, J.L.; Ward, W.K.; Beard, J.C.; Palmer, J.P. Quantification of the relationship between insulin sensitivity and β-cell function in human subjects: Evidence for a hyperbolic function. *Diabetes* **1993**, *42*, 1663–1672. [CrossRef] [PubMed]
29. Yu, B.; Sun, Y.; Wang, Y.; Wang, B.; Tan, X.; Lu, Y.; Zhang, K.; Wang, N. Associations of artificially sweetened beverages, sugar-sweetened beverages, and pure fruit/vegetable juice with visceral adipose tissue mass. *Diabetes Metab. Syndr.* **2023**, *17*, 102871. [CrossRef] [PubMed]
30. Geidl-Flueck, B.; Hochuli, M.; Németh, Á.; Eberl, A.; Derron, N.; Köfeler, H.C.; Tappy, L.; Berneis, K.; Spinas, G.A.; Gerber, P.A. Fructose- and sucrose- but not glucose-sweetened beverages promote hepatic de novo lipogenesis: A randomized controlled trial. *J. Hepatol.* **2021**, *75*, 46–54. [CrossRef] [PubMed]
31. Stanhope, K.L.; Schwarz, J.M.; Keim, N.L.; Griffen, S.C.; Bremer, A.A.; Graham, J.L.; Hatcher, B.; Cox, C.L.; Dyachenko, A.; Zhang, W.; et al. Consuming fructose-sweetened, not glucose-sweetened, beverages increases visceral adiposity and lipids and decreases insulin sensitivity in overweight/obese humans. *J. Clin. Investig.* **2009**, *119*, 1322–1334. [CrossRef] [PubMed]
32. Tucker, L.A. Fiber intake and insulin resistance in 6374 adults: The role of abdominal obesity. *Nutrients* **2018**, *10*, 237. [CrossRef] [PubMed]
33. Weickert, M.O.; Roden, M.; Isken, F.; Hoffmann, D.; Nowotny, P.; Osterhoff, M.; Blaut, M.; Alpert, C.; Gögebakan, Ö.; Bumke-Vogt, C.; et al. Effects of supplemented isoenergetic diets differing in cereal fiber and protein content on insulin sensitivity in overweight humans. *Am. J. Clin. Nutr.* **2011**, *94*, 459–471. [CrossRef] [PubMed]
34. Lissner, L.; Troiano, R.P.; Midthune, D.; Heitmann, B.L.; Kipnis, V.; Subar, A.F.; Potischman, N. OPEN about obesity: Recovery biomarkers, dietary reporting errors and BMI. *Int. J. Obes.* **2007**, *31*, 956–961. [CrossRef] [PubMed]
35. Huang, K.; Yu, D.; Guo, Q.; Yang, Y.; Wei, X.; Zhao, L.; Fang, H. Validation of the MSM and NCI method for estimating the usual intake of nutrients and food according to four seasons of seven consecutive daily 24 hour dietary recalls in Chinese adults. *Nutrients* **2022**, *14*, 445. [CrossRef] [PubMed]
36. Tooze, J.A.; Midthune, D.; Dodd, K.W.; Freedman, L.S.; Krebs-Smith, S.M.; Subar, A.F.; Guenther, P.M.; Carroll, R.J.; Kipnis, V. A new statistical method for estimating the usual intake of episodically consumed foods with application to their distribution. *J. Am. Diet. Assoc.* **2006**, *106*, 1575–1587. [CrossRef] [PubMed]
37. Altman, D.G.; Bland, J.M. Absence of evidence is not evidence of absence. *BMJ* **1995**, *311*, 485. [CrossRef] [PubMed]
38. Lee, D.-H.; Park, K.S.; Ahn, S.; Ku, E.J.; Jung, K.Y.; Kim, Y.J.; Kim, K.M.; Moon, J.H.; Choi, S.H.; Park, K.S.; et al. Comparison of abdominal visceral adipose tissue area measured by computed tomography with that estimated by bioelectrical impedance analysis method in Korean subjects. *Nutrients* **2015**, *7*, 10513–10524. [CrossRef] [PubMed]

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