Adherence to a caloric budget and body weight change vary by season, gender, and BMI: An observational study of daily users of a mobile health app

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Abstract

Objective: Self-monitoring, one of the most important behaviors for successful weight loss, can be facilitated through mobile health applications (mHealth apps). Therefore, it is of interest to determine whether consistent users of these apps succeed in achieving their weight goals. This study used data from an mHealth app that enabled tracking of caloric intake, body weight, and physical activity and provided a caloric budget depending on weight goal. The primary objective was to evaluate adherence to caloric budget and body weight change among the most consistent (i.e., daily) trackers of caloric intake over a calendar year (n = 9372, 50% male).

Methods: Gender-stratified linear mixed models were conducted to examine the effects of quarter of year (Q1–Q4 as season proxies) and body mass index (BMI) group (normal weight, overweight, obesity) on adherence to a caloric budget (kcal/day). Change in body weight was analyzed using a subset of users (n = 5808) who entered their weight in the app at least once per week, once per month, or once in Q1 and Q4. Physical activity entries were evaluated in exploratory analyses.

Results: Only users with obesity met their caloric budget in Q1. Deviation from budget increased for all groups from Q1 to Q2 (mean change±standard error of the mean: +23.7±1.8 and +39.7±2.2 kcal/day for female and male users, p < 0.001), was stable between Q2 and Q3, and fluctuated thereafter depending on gender and BMI, with greater deviation among males with overweight. Users with obesity with weight entries at least once per month lost the most weight (−6.1±0.3 and −4.5 [±0.3] kg for females and males, p < 0.001). Physical activity was highest in the summer months.

Conclusions: Among consistent caloric trackers, adherence to a caloric budget and body weight vary by season, gender, and BMI. Self-monitoring of body weight in addition to caloric tracking may lead to improved weight loss outcomes.

KEYWORDS

caloric restrictions, energy intake, self-monitoring, weight management
1 | INTRODUCTION

Mobile health applications (mHealth apps) have grown in popularity, with more than 50,000 mHealth apps available for download on Apple and Google Play stores in early 2021. Many mHealth apps are designed for weight management and provide their users with a caloric budget to stay within depending on their weight goal. They also enable self-monitoring of intake of kilocalories (subsequently referred to as calories), adherence to the caloric budget, nutrient intakes, body weight, and physical activity. Use of weight management apps appears to result in a decrease in body weight, at least in the short term, likely attributable to improved adherence to self-monitoring demonstrated with mHealth apps compared to other behavioral weight management interventions (e.g., web-based or paper food intake diaries). This increased adherence seems to be a major contributing factor to their effectiveness, as research has consistently shown that self-monitoring of diet, weight, and physical activity is one of the most important behaviors for successful weight loss.

While most evaluations of the impact of dietary self-monitoring on weight loss have been performed in intervention studies using small and homogeneous samples of individuals, generally targeting one gender only, data from real-world mHealth apps can provide a substantial amount of information on individuals from larger and potentially more diverse populations who adhere to self-monitoring behaviors for long periods of time in their natural day-to-day settings. Despite the widespread use of these apps, no previous study has investigated the temporal dynamics of caloric intake, body weight, and physical activity among daily, long-term app users (hereafter referred to as users). It is therefore of interest to determine whether individuals who have developed a sustained daily habit of using a weight management app succeed in achieving their long-term goals.

Furthermore, temporal analyses are relevant as seasonal effects have been reported to relate to food intake, physical activity, and body weight. Indeed, interest in diets and weight loss in the general population seems to peak early during a calendar year, likely being linked to common health-related New Year’s resolutions. In addition, changes in the type of foods selected for consumption throughout the year have been associated with seasonal variations in diet, with lower adherence to dietary guidelines in warmer months largely associated with a decreased preference for legumes and nuts and an increased preference for sugar-containing beverages and dairy products during that time of year. While seasonality of food consumption may reflect food product availability and prices at different times of the year, evidence suggests that social and cultural norms (e.g., holidays, lifestyle patterns in different seasons) play a greater role in developed countries.

Among individuals who are actively seeking to lose or maintain weight, weight loss mainly occurs early in the year, and holidays at the end of a year may lead to weight gain due to increased gatherings where food can be abundant. Seasonal changes in body weight may also be explained by a generally lower level of physical activity during colder times of the year. Lastly, assessing self-monitoring patterns and outcomes by gender and body mass index (BMI) group is important due to physiological considerations of body composition, varied responses to (and experiences with) weight loss interventions, and lack of gender comparisons regarding self-monitoring and weight loss in previous studies (for a review, see Burke et al.).

Therefore, this study aimed to examine variations in adherence to a caloric budget and body weight change over a calendar year among users of a popular mHealth app who recorded their caloric intake daily. Outcomes were compared by quarter of the year (as a proxy for season) across gender and BMI groups, and patterns of physical activity were also explored. It was hypothesized that adherence to a caloric budget would be highest in the first quarter of the year because of presumed higher motivation at this time, and that users with more frequent weight entries (indicating higher self-monitoring) would have greater net change in body weight.

2 | METHODS

2.1 | Study population and data

A de-identified dataset was provided by a company who developed a popular mHealth app for weight loss/management. The company requested not to be identified in the manuscript. Ethics approval for this study was obtained from the McGill University Faculty of Agricultural and Environmental Sciences Research Ethics Board 19-11-071. The app was available in English only at the time of data collection. The dataset included entries of all food items and daily caloric intake, body weight values, and physical activity information recorded by users of the app residing in the United States and Canada over a 12-month period from 1 January 2016 to 31 December 2016. A variable for caloric budget was also available, which was obtained from each user’s estimated basal metabolic rate (calculated with the Mifflin-St Jeor equation based on weight, height, age, and gender), their physical activity level, and the number of pounds they wanted to lose every week (if any). The calorie budget was calculated by the app with the consideration that losing 1 pound (0.45 kg) requires a calorie deficit of 3500 kcal. The budget changed according to users’ updates to body weight, age, and goal weight. Body weight could be self-entered in the app or synchronized with weight data from a smart scale.

Physical activity could be logged by choosing among several activity options. The number of calories expended was estimated according to the type of activity and its duration based on the Compendium of Physical Activities. Similar to weight, physical activity data could also be synchronized from wearable fitness trackers. Users could choose to accept or disable push notifications that reminded them to log food or weight. Data on the proportion of selected users with push notifications were not available, but this was considered inconsequential since the present study involved users who tracked calories daily.
Nearly four million individuals logged at least one food item in the app at some point during 2016. However, separate analyses of data from the mHealth app used in the present study have reported steep declines in user engagement with the app after a short-term period (70%-90% reduce/stop app use within 3–6 months. From this it is conceivable that a large proportion of users who download such an app test it for a short period (e.g., a few days/weeks) without continued engagement. To investigate the study objectives among consistent app users, the subset of users who recorded their caloric intake daily for the entire year was selected.

A total of 9847 users were available based on this selection, but some exclusions were applied according to missing data or being aged <18 (full details are presented in Figure S1). Users with underweight (BMI < 18.5 kg/m² at baseline) were also excluded due to potential differences in motivations for using an mHealth app among this group. Furthermore, users with average daily caloric intake lower than 500 kcal/day or greater than 4000 kcal/day for 3 months or more were excluded (intakes outside of these values are defined as extreme and considered implausible). Lastly, because some values of daily energy expended from activity were implausible, data from users who had a value greater than 3.29 standard deviations (SDs) above the average daily energy expended from activity for 1 month or more were excluded from analyses pertaining to physical activity (but not from analyses pertaining to adherence to caloric budget and body weight). This choice was made based on Tabachnick and Fidell’s indication that cases with a Z-score of more than 3.29 can be considered as univariate outliers among continuous variables.

2.2 Statistical analysis

All analyses were stratified by gender given the potentially confounding impact of this factor. It should be noted that the term gender as well as the female and male categories are used here in conformity with the terms that were displayed to the users of the app when they logged their sociodemographic information upon app sign-up. The effect of baseline BMI was investigated on all outcomes because of potential differences in the amount of weight that users could lose or may have desired to lose (or maintain) across BMI groups. BMI categories that were evaluated included normal weight (BMI ≥ 18.5 kg/m² and < 25.0 kg/m² at baseline), overweight (BMI ≥ 25.0 kg/m² and < 30.0 kg/m² at baseline), and obesity (BMI ≥ 30.0 kg/m² at baseline).

Although all users of the sample entered their food intake in the app every day, not all users entered their weight consistently. Therefore, subgroups of users were compared based on how often they recorded their weight in the app as follows: once per week or more (Subgroup 1); less than once per week, but at least once per month (Subgroup 2); or less than once per month, but at least once in Q1 and Q4 (Subgroup 3). Descriptive statistics were computed for user characteristics by BMI group and were compared within each gender using one-way analyses of variance. These analyses were performed for the complete sample as well as for each subgroup. In addition, factorial analyses of variance were conducted to evaluate the main effect of subgroups and its potential interaction with BMI category for each continuous variable. Chi-square tests of independence were also conducted to compare the distribution of users from each gender and BMI category across the three subgroups. Furthermore, the characteristics of users from each subgroup were compared to those of the complete sample using one-sample t-tests (for continuous variables) and chi-square goodness of fit tests (for categorical variables).

The primary outcome of interest was adherence to a caloric budget, assessed by subtracting users’ mean caloric budget from their mean caloric intake (in kcal/day). The resulting value was averaged by quarter (Q) as a proxy for season: Q1 = winter (January–March), Q2 = spring (April–June), Q3 = summer (July–September), and Q4 = fall (October–December). Calorie-related analyses were conducted on the entire sample of users. Net change in body weight (in kg) from Q1 to Q4 was a secondary outcome of interest. Weight-related analyses were conducted using the three subgroups of users varying in frequency of weight entries in the app. Monthly averages of physical activity (in kcal/day) were evaluated for the complete sample in exploratory analyses to facilitate fine-grained interpretation of patterns of caloric intake and body weight with consideration of physical activity; however, some users may have engaged in activity without tracking this information in the app. Quarterly comparisons of caloric intake are discussed herein given the objective to evaluate seasonal patterns and the potential for shorter term variations in caloric intake to be compensated for by metabolic adaptations. Nevertheless, monthly comparisons of deviation from caloric budget and caloric intake are also presented in Figures S2 and S3, respectively.

Linear mixed models were used to examine the effects of BMI group, quarter, and their interaction on each dependent variable of interest with a split-plot design. Analyses conducted on net weight change were also stratified by frequency of weight input according to the three subgroups described above. The between-subjects factor of each model was BMI group and had three levels: normal weight, overweight, or obesity. The within-subject factor was the quarter of the calendar year. For analyses examining deviation from caloric budget, this factor had four levels (Q1–Q4). For analyses evaluating body weight, this factor had two levels (Q1 vs. Q4) to evaluate net change in weight over the year, given the fact that all users had weight entries available in these quarters (but not all users had weight entries available in each quarter). The averages for dependent variables of interest were adjusted for two covariates: reliability and age. Reliability was a time-varying covariate entered in the analyses that evaluated adherence to caloric budget. It refers to the percentage of days of the quarter for which food records were considered complete.

In line with previous studies interested in dietary tracking with smartphone apps, days with at least 800 kcal recorded were considered as reliable. The reliability covariate was used to account for the potential for underreporting of food intake, which is common in studies that require participants to self-report their dietary intake. However, it should be acknowledged that the
individuals in the present analysis were not research participants and thus the presence of underreporting may be lower. Nevertheless, the reliability covariate was employed to acknowledge the fact that there may be days with incomplete recordings even among users who input food intake daily. Age on 1 January was used as a continuous covariate in weight-related analyses. Exploratory post hoc comparisons of gender differences by BMI category in mean weight loss goal, deviation from budget by quarter, net change in body weight over the year, and physical activity were performed using independent t-tests.

All analyses were performed using SPSS 27 (IBM Corp.). The Toeplitz matrix was used as the covariance structure as it yielded the smallest Akaike’s Information Criteria among three structures that were evaluated (Compound symmetry, Autoregressive 1, and Toeplitz). The denominator for degrees of freedom was calculated with the Satterthwaite approximation. The models were fit using restricted maximum-likelihood estimation. An alpha level of 0.01 was used to account for the potential of type 1 errors due to multiple testing.

3 | RESULTS

3.1 | Characteristics of the complete sample

From the initial sample of 9847 users, 475 were excluded from all analyses based on the exclusion criteria described above. The final sample size for the analysis of adherence to caloric budget was 9372 (4670 female and 4702 male). The final sample size for the exploratory analysis of energy expended through physical activity was 9129 (4544 female and 4585 male) because data from 126 female and 117 male users were further excluded from the complete sample due to implausible values. Table 1 presents the descriptive statistics of the complete sample according to gender and BMI group.

The median start year of app use was 2013 (range: 2009–2015). The mean age (±SD) was 46.8 (±13.7) years among female users and 50.2 (±13.1) years among male users. Among female users, 50%, 26%, and 24% were classified as having normal weight, overweight, and obesity, respectively. Among male users the BMI group proportions were 30%, 42%, and 28%, respectively. The reliability of the caloric intake data for the complete year was very high (93.8% [SD = 13.0%] or above). Across BMI groups, the number of weight entries was similar for male users, $F(2, 4699) = 2.04, p = 0.130$, as was daily caloric intake for female users, $F(2, 4667) = 3.00, p = 0.050$. The main effect of BMI was significant in all other analyses ($p < 0.009$). Pairwise comparisons were therefore conducted to determine which means significantly differed (see Table 1).

Briefly, pairwise comparisons showed that users with normal weight were younger than the other BMI groups, regardless of gender. Female users with normal weight had significantly fewer weight entries in the app compared to those with obesity. The mean

| TABLE 1 | Descriptive statistics of the complete sample according to gender and BMI category |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | Female | | Male |
| | Normal | Overweight | Obese | Normal | Overweight | Obese |
| Complete sample: users who logged at least one food item in the app every day ($n = 9372$) | | | | | | | |
| Number of users (% within each gender) | 2347 (50.3%) | 1221 (26.1%) | 1102 (23.6%) | 1410 (30.0%) | 1973 (42.0%) | 1319 (28.1%) |
| Age (years) | $45.4^a ± 13.7$ | $48.2^b ± 13.8$ | $48.0^b ± 13.4$ | $48.9^a ± 13.7$ | $50.6^b ± 12.8$ | $50.9^b ± 13.0$ |
| Baseline BMI (kg/m²) | $22.0^a ± 1.7$ | $27.2^b ± 1.4$ | $36.4^a ± 6.1$ | $23.2^a ± 1.4$ | $27.2^b ± 1.4$ | $35.0^a ± 5.1$ |
| Baseline weight (kg) | $59.6^a ± 6.6$ | $73.6^b ± 7.3$ | $98.3^a ± 18.8$ | $74.3^a ± 7.3$ | $87.1^b ± 8.2$ | $112.6^a ± 18.9$ |
| Goal weight (kg) | $57.7^a ± 6.5$ | $66.2^b ± 8.3$ | $76.9^a ± 15.4$ | $73.5^a ± 7.9$ | $81.9^b ± 8.7$ | $94.4^a ± 15.0$ |
| Weight loss goal (kg) | $1.9^a ± 3.7$ | $7.4^a ± 6.4$ | $21.4^a ± 15.8$ | $0.8^a ± 4.4$ | $5.2^b ± 5.7$ | $18.2^a ± 14.3$ |
| Number of weight entries | $71.7^a ± 116.5$ | $77.8^a ± 116.9$ | $87.9^b ± 121.0$ | $93.6^a ± 128.4$ | $87.7 ± 122.1$ | $84.3 ± 120.3$ |
| Daily caloric intake (kcal/day) | $1544.6^a ± 385.5$ | $1514.7^b ± 373.4$ | $1550.2^b ± 433.6$ | $2116.5^a ± 493.4$ | $2082.4 ± 483.6$ | $2057.1^b ± 515.4$ |
| Reliability (%) | $95.2^a ± 12.3$ | $94.9 ± 11.3$ | $93.8^b ± 13.0$ | $98.6^a ± 5.3$ | $98.5^b ± 5.4$ | $97.7^a ± 7.2$ |
| Daily budget (kcal/day) | $1412.8^a ± 279.5$ | $1393.9^a ± 260.4$ | $1518.8^b ± 333.6$ | $1985.7^a ± 348.2$ | $1920.3^b ± 339.4$ | $2012.2^a ± 376.0$ |
| Daily energy expended from activity (kcal/day) | $251.9^a ± 223.1$ | $232.7^a ± 205.1$ | $205.1^b ± 204.1$ | $347.9^a ± 294.0$ | $354.9^a ± 299.7$ | $291.6^b ± 279.0$ |

Note: Number of users (% within each gender): frequency of users in each BMI category and corresponding percentage of users within each gender (percentages may not total to 100% due to rounding). Age, baseline BMI, baseline weight, goal weight, weight loss goal: mean value (±SD) on 1 January 2016. Number of weight entries, daily caloric intake, reliability, daily budget, and daily energy expended from activity: mean value (±SD) for the entire year. The mean value of each continuous variable was compared across BMI categories (for each gender separately), and pairwise comparisons were conducted in the presence of a significant main effect of BMI. Different letter superscripts (a, b, or c) for means associated with a given gender within a single row indicate a statistically significant difference with an alpha level of 0.01.
difference (±SD) between baseline weight and goal weight was approximately 1.5 (±4.0) kg for users with normal weight, 6.0 (±6.0) kg for users with overweight, and 19.7 (±15.1) kg for users with obesity, with higher weight loss goals being input by female users (p < 0.001 for all BMI categories). Daily caloric intake was significantly greater among male users with normal weight than for those with obesity. Daily caloric budget was significantly greater for female users with obesity compared to the normal weight and overweight groups, while among males, users with overweight had the lowest daily caloric budget compared to the normal weight and obesity BMI groups. Overall, users with obesity had the lowest levels of physical activity and reliability of caloric intake entries, regardless of gender.

### 3.2 Characteristics of the three subgroups

Table 2 presents the distribution of users from the complete sample according to their frequency of weight entries. The subset of users included in weight-related analyses was composed of the 5808 individuals (2899 female and 2909 male) who logged their weight in the app at least once in Q1 and Q4. These users were distributed among Subgroup 1 (n = 1371), Subgroup 2 (n = 1767), and Subgroup 3 (n = 2670). Among the 126 female users who were excluded from the analysis pertaining to physical activity, 28, 20, and 37 were also in Subgroups 1, 2, and 3, respectively. Similarly, among the 117 male users who were excluded from this analysis, 21, 21, and 36 were also in Subgroups 1, 2, and 3, respectively. The characteristics of each subgroup according to gender and BMI category are shown in Table 3.

The proportion of female users (which varied from 46% to 54%) was significantly different between the three subgroups (p < 0.001). In addition, the distribution of users across BMI categories was statistically equivalent between subgroups for female users (p = 0.013), but not for male users (p = 0.002). Nevertheless, in all subgroups, the most prevalent BMI category was the normal weight category for female users and the overweight category for male users. User characteristics expressed by continuous variables were not always equivalent across BMI categories, depending on gender and subgroup. When the main effect of BMI was significant, pairwise comparisons were conducted to determine which means were different. The results of these comparisons are presented in Table 3.

As expected, the number of weight entries in the app decreased significantly from Subgroup 1 to Subgroup 3 for female and male users (all p < 0.001). For both genders, daily budget, reliability, weight loss goal, and daily physical activity were shown to be similar across subgroups (all p > 0.029), except for reliability in Subgroup 1 which was about 1% lower than in the other subgroups for male users (all p ≤ 0.003). Among female users, age decreased significantly from Subgroup 1 to Subgroup 3 (all p ≤ 0.003). A similar pattern was observed for male users, but the difference between Subgroups 2 and 3 was not statistically significant (p = 0.044). Female users with obesity from Subgroup 1 had smaller values for baseline BMI, baseline weight, and goal weight than those from the other subgroups (all p < 0.001), but no subgroup differences were observed for those variables otherwise (all p ≥ 0.012). Daily caloric intake was higher in Subgroup 2 than in Subgroup 1 for female users (p = 0.001), whereas it was higher in Subgroup 2 than in the two other subgroups for male users (all p ≤ 0.010).

Overall, the sociodemographic characteristics were similar across subgroups, with the most prevalent differences being related to age (and, of course, to the number of weight entries since subgroups were divided based on that variable). Despite being statistically significant, those differences in age should have fairly minor consequences as users from the three subgroups are still within the same decades.

### Table 2 Distribution of users in the complete sample according to their frequency of weight entries as a function of gender and BMI category

| Female | Normal | Overweight | Obese | Male | Normal | Overweight | Obese | Total | % of total sample |
|--------|--------|------------|-------|------|--------|------------|-------|-------|------------------|
| Everyday | 13 | 16 | 13 | 15 | 18 | 6 | 81 | 1 |
| At least once per week | 301 | 147 | 146 | 224 | 277 | 195 | 1290 | 14 |
| At least once per month | 352 | 219 | 249 | 294 | 409 | 244 | 1767 | 19 |
| At least once per quarter | 506 | 299 | 283 | 217 | 379 | 296 | 1980 | 21 |
| At least once in Q1 and Q4 | 192 | 96 | 67 | 93 | 158 | 84 | 690 | 7 |
| At one or more other times of the year | 715 | 342 | 272 | 420 | 547 | 362 | 2658 | 28 |
| Never | 268 | 102 | 72 | 147 | 185 | 132 | 906 | 10 |
| Total | 2347 | 1221 | 1102 | 1410 | 1973 | 1319 | 9372 | 100 |

Note: Each user is considered in only one category of frequency of weight entries (i.e., the first category that applies from the top to the bottom of the table).

Abbreviation: Q, quarter.
## Table 3: Descriptive statistics of the three weight entry frequency subgroups according to gender and BMI category

| Subgroup 1: users who logged their weight at least once per week (n = 1371) | Female | Male |
|---|---|---|
| Number of users (% within each gender) | Normal | Overweight | Obese | Normal | Overweight | Obese |
| 314 (49.4%) | 163 (25.6%) | 159 (25.0%) | 239 (32.5%) | 295 (40.1%) | 201 (27.3%) |
| Age (years) | 51.5 ± 12.1 | 51.6 ± 12.7 | 49.1 ± 12.7 | 52.5 ± 12.5 | 53.7 ± 12.1 | 52.6 ± 12.1 |
| Baseline BMI (kg/m²) | 22.2 ± 1.6 | 27.1 ± 1.4 | 35.2 ± 4.8 | 23.1 ± 1.4 | 27.0 ± 1.4 | 34.8 ± 5.1 |
| Baseline weight (kg) | 59.4 ± 6.3 | 73.2 ± 7.4 | 94.7 ± 14.0 | 74.0 ± 7.4 | 86.6 ± 8.0 | 111.2 ± 16.9 |
| Goal weight (kg) | 57.7 ± 6.2 | 65.1 ± 8.0 | 73.2 ± 13.8 | 73.0 ± 7.8 | 81.2 ± 8.2 | 92.3 ± 13.6 |
| Weight loss goal (kg) | 1.7 ± 3.5 | 8.1 ± 6.9 | 21.5 ± 13.0 | 1.0 ± 4.1 | 5.4 ± 5.3 | 18.9 ± 14.9 |
| Number of weight entries | 320.3 ± 65.5 | 324.5 ± 66.5 | 325.6 ± 62.6 | 314.7 ± 69.3 | 315.4 ± 67.0 | 312.1 ± 70.4 |
| Daily caloric intake (kcal/day) | 1513.3 ± 385.9 | 1525.4 ± 392.5 | 1510.3 ± 364.2 | 2118.1 ± 552.5 | 2067.3 ± 490.8 | 2012.1 ± 519.3 |
| Reliability (%) | 94.1 ± 13.6 | 94.8 ± 10.1 | 94.6 ± 12.1 | 98.1 ± 6.7 | 98.0 ± 8.1 | 97.1 ± 9.1 |
| Daily budget (kcal/day) | 1390.6 ± 252.9 | 1364.5 ± 276.0 | 1467.9 ± 293.3 | 1957.2 ± 345.8 | 1903.0 ± 356.2 | 1959.8 ± 372.9 |
| Daily energy expended from activity (kcal/day) | 253.2 ± 228.1 | 249.3 ± 213.9 | 225.7 ± 233.0 | 370.9 ± 311.8 | 335.9 ± 301.6 | 284.0 ± 270.9 |

| Subgroup 2: users who logged their weight at least once per month (n = 1767) | Female | Male |
|---|---|---|
| Number of users (% within each gender) | 352 (42.9%) | 219 (26.7%) | 249 (30.4%) | 294 (31.0%) | 409 (43.2%) | 244 (25.8%) |
| Age (years) | 47.2 ± 12.9 | 48.5 ± 14.3 | 46.3 ± 12.6 | 49.1 ± 13.5 | 50.4 ± 12.5 | 49.0 ± 13.0 |
| Baseline BMI (kg/m²) | 22.2 ± 1.7 | 27.3 ± 1.4 | 37.0 ± 6.6 | 23.1 ± 1.4 | 27.1 ± 1.5 | 34.7 ± 5.1 |
| Baseline weight (kg) | 60.3 ± 6.4 | 73.9 ± 7.3 | 100.7 ± 20.9 | 74.6 ± 7.6 | 86.7 ± 8.1 | 112.2 ± 19.8 |
| Goal weight (kg) | 57.8 ± 5.9 | 66.5 ± 7.9 | 77.2 ± 17.7 | 73.5 ± 8.2 | 80.6 ± 8.0 | 93.5 ± 14.9 |
| Weight loss goal (kg) | 2.5 ± 3.5 | 7.4 ± 6.4 | 23.5 ± 16.6 | 1.1 ± 4.2 | 6.1 ± 5.0 | 18.7 ± 14.0 |
| Number of weight entries | 124.1 ± 92.9 | 121.8 ± 91.5 | 123.0 ± 96.9 | 151.2 ± 100.2 | 140.7 ± 95.9 | 130.3 ± 98.4 |
| Daily caloric intake (kcal/day) | 1618.7 ± 379.5 | 1564.6 ± 395.1 | 1571.4 ± 432.8 | 2195.3 ± 437.6 | 2148.5 ± 471.8 | 2124.2 ± 507.5 |
| Reliability (%) | 96.7 ± 10.0 | 96.1 ± 8.3 | 93.7 ± 12.8 | 99.4 ± 1.9 | 98.7 ± 4.4 | 98.3 ± 4.2 |
| Daily budget (kcal/day) | 1400.7 ± 275.7 | 1414.7 ± 238.1 | 1498.4 ± 318.3 | 1984.0 ± 331.0 | 1893.6 ± 329.7 | 2009.8 ± 353.1 |
| Daily energy expended from activity (kcal/day) | 243.3 ± 209.6 | 233.8 ± 208.1 | 213.6 ± 184.7 | 368.0 ± 289.1 | 351.3 ± 294.0 | 312.5 ± 298.8 |

| Subgroup 3: Users who logged their weight at least once in Q1 and Q4 (n = 2670) | Female | Male |
|---|---|---|
| Number of users (% within each gender) | 698 (48.4%) | 395 (27.4%) | 350 (24.3%) | 310 (25.3%) | 537 (43.8%) | 380 (31.0%) |
| Age (years) | 43.7 ± 14.2 | 46.3 ± 13.9 | 46.4 ± 13.8 | 46.8 ± 13.5 | 48.8 ± 12.8 | 49.5 ± 13.3 |
| Baseline BMI (kg/m²) | 22.0 ± 1.7 | 27.2 ± 1.4 | 36.6 ± 6.0 | 23.3 ± 1.3 | 27.3 ± 1.4 | 35.2 ± 5.2 |
| Baseline weight (kg) | 59.5 ± 6.8 | 73.8 ± 7.7 | 98.9 ± 18.3 | 74.2 ± 7.3 | 87.8 ± 8.2 | 113.3 ± 19.6 |
| Goal weight (kg) | 57.6 ± 6.3 | 66.8 ± 8.0 | 77.7 ± 14.5 | 73.2 ± 7.9 | 82.3 ± 8.4 | 94.2 ± 16.3 |
| Weight loss goal (kg) | 1.9 ± 3.7 | 7.0 ± 5.4 | 21.2 ± 15.6 | 1.0 ± 4.0 | 5.5 ± 5.3 | 19.1 ± 14.0 |
| Number of weight entries | 28.2 ± 41.5 | 30.6 ± 36.9 | 33.3 ± 39.0 | 32.4 ± 48.0 | 33.4 ± 47.8 | 33.5 ± 43.2 |
| Daily caloric intake (kcal/day) | 1561.9 ± 385.6 | 1531.9 ± 356.9 | 1565.0 ± 445.5 | 2127.6 ± 429.3 | 2099.8 ± 490.0 | 2083.3 ± 488.2 |
| Reliability (%) | 95.6 ± 10.6 | 95.5 ± 11.4 | 93.7 ± 13.1 | 98.9 ± 3.8 | 98.6 ± 4.9 | 98.1 ± 6.8 |
| Daily budget (kcal/day) | 1411.4 ± 279.3 | 1399.7 ± 267.6 | 1521.5 ± 340.2 | 1956.1 ± 328.5 | 1914.1 ± 338.5 | 1999.8 ± 370.7 |
3.3 Comparison of subgroups with the complete sample

The proportion of female users was 46%, 46%, and 54% in Subgroups 1, 2, and 3, respectively. These proportions were compared to that observed in the complete sample, where 50% of users are females. The analysis showed that the distribution of users between genders was similar to that of the complete sample in Subgroup 1 (p = 0.011), but not in Subgroups 2 and 3 (all p ≤ 0.004). Moreover, the distribution of users between BMI groups was equivalent to that of the complete sample for female users in Subgroups 1 and 3 as well as for male users in Subgroups 1 and 2 (all p ≥ 0.271). In Subgroup 2, however, there were fewer female users with normal weight and more female users with obesity in comparison with the complete sample (p < 0.001). A similar pattern was observed for male users in Subgroup 3 (p = 0.001). To further evaluate the representativeness of each subgroup in relation to the complete sample, the mean value of each continuous variable within in each subgroup was compared to the homologous mean in the complete set of app users.

In all subgroups, the mean number of weight entries differed significantly from the corresponding mean in the complete sample, regardless of gender and BMI category (all p < 0.001). In Subgroup 1, female and male users with normal weight and overweight were significantly older than when considering the same groups in the complete sample (all p ≤ 0.001). In addition, female users with obesity had a significantly lower baseline BMI, baseline weight, and goal weight (all p ≤ 0.003). In Subgroup 2, female users with normal weight had a larger weight loss goal than the analogous group in the complete sample (p = 0.005). Male users with overweight also had a higher weight loss goal as well as a lower goal weight (all p ≤ 0.001). Daily caloric intake was higher than in the complete sample for male users with overweight as well as for female and male users with normal weight (all p ≤ 0.005). The latter two groups also had more reliable caloric intake entries (all p ≤ 0.005). In Subgroup 3, the only remaining differences observed in relation to the complete sample were that female users with normal weight as well as male users with normal weight and overweight were significantly younger than the corresponding groups in the complete sample (all p ≤ 0.006).

3.4 Adherence to caloric budget over time

Given the equivalence of the patterns of results with and without adjustment, all following statistical analyses are presented for adjusted models only. The average values of deviation from caloric budget are presented in Figure 1. Apart from users with obesity in Q1, users were over budget throughout the year. A significant interaction between quarter and BMI was observed for female and male users, F(6, 6265) = 6.22, p < 0.001, and F(6, 6437) = 3.19, p = 0.004, respectively. The decomposition of the interactions showed that the effect of quarter was significant for all BMI groups among both female and male users (all p < 0.001), hence all groups varied in their ability to remain on budget throughout the year. However, pairwise comparisons revealed that time did not have the same impact on adherence to budget in all BMI categories.

Overall, the deviation from budget significantly increased between Q1 and Q2 (mean change ± standard error of the mean; SEM): +23.7 ± 1.8 kcal/day and +39.7 ± 2.2 kcal/day on average for female and male users, respectively, all p < 0.001 and then remained stable between Q2 and Q3 (all p ≥ 0.031). The interaction between quarter and BMI was attributable to the fact that the values also remained stable between Q3 and Q4 for all users (all p ≥ 0.081) except for females and males with obesity, who continued to stray from their budget (mean change ± SEM): +14.0 ± 3.6 kcal/day for female and +11.8 ± 4.2 kcal/day for male users, both p ≤ 0.005). As illustrated in Figure 1, there was a greater increase in deviation from budget from the beginning to the end of the year in the group of users with obesity (mean change ± SEM): +49.4 ± 5.5 kcal/day for female and +65.1 ± 6.0 kcal/day for male users) than in the group with normal weight (mean change ± SEM): +16.7 ± 3.8 kcal/day for female and +33.1 ± 5.8 kcal/day for male users) and overweight (mean change ± SEM): +13.9 ± 5.2 kcal/day for female and +42.1 ± 4.9 kcal/day for male users). Nevertheless, the amount of deviation from budget was greater in Q4 than in Q1 for all BMI categories (all p ≤ 0.008).

The decomposition of the significant interaction also revealed that individuals with obesity remained closer to their budget than the other BMI groups at all times (all p < 0.001 for female and male users). However, consistent with the significant BMI × quarter interaction observed, the gap between the values of the three BMI groups...
tended to decrease as the year went by. For comparison purposes, the net value of daily caloric intake \((\text{in kкал/день})\) is shown in Figure S4. The effect of time on average caloric intake was similar to its effect on the deviation from budget. Exploratory post hoc analyses revealed that there were no significant gender differences in deviation from budget in any quarter for users with normal weight and obesity \((p > 0.195)\). For users with overweight, no gender difference was observed in Q1 \((p = 0.128)\). However, among users with overweight, males had a significantly higher mean deviation from budget compared to females in Q2 \(\text{(mean deviation [±SEM]:} +127.7 [±9.7] \text{kкал/день для мужчин и} +170.5 [±10.0] \text{kкал/день для женщин,} p = 0.004)\), Q3 \(\text{(mean deviation [±SEM]:} +125.0 [±9.7] \text{kкал/день для мужчин и} +167.2 [±10.0] \text{kкал/день для женщин,} p = 0.004)\), and Q4 \(\text{(mean deviation [±SEM]:} +119.1 [±9.7] \text{kкал/день для мужчин и} +169.8 [±10.0] \text{kкал/день для женщин,} p = 0.001)\).

### 3.5 | Body weight over time

Table 4 presents the mean body weight in Q1 and Q4 as well as the change in body weight (net change and % from baseline) between these quarters of the year according to BMI category, gender, and weight entry frequency subgroup. A significant interaction was observed between quarter and BMI for female and male users from Subgroup 1, \(F(2, 633) = 84.50, p < 0.001\) and \(F(2, 732) = 40.90, p < 0.001\), respectively. The interaction between quarter and BMI was also significant in Subgroup 2, \(F(2, 817) = 87.72, p < 0.001\) and \(F(2, 944) = 61.53, p < 0.001\), as well as in Subgroup 3, \(F(2, 1440) = 64.07, p < 0.001\) and \(F(2, 1224) = 54.38, p < 0.001\), for female and male users, respectively. This interaction was driven by the fact that time had a different impact on weight across BMI groups.

The results of the pairwise comparisons between Q1 and Q4 are presented in Table 4. Female users with overweight or obesity in all subgroups lost a significant amount of weight between these quarters, the mean weight loss \((\pm \text{SEM})\) being \(-3.0 (\pm 0.1) \text{ kg}\). Female users with obesity lost the most weight \((-4.7 (\pm 0.2) \text{ kg overall})\), and the magnitude of their weight loss was approximately twice as large in Subgroups 1 and 2 than in Subgroup 3. Among male users in all subgroups, no change in weight was observed for individuals with normal weight and overweight, but there was a significant loss of \(-4.3 (\pm 0.1) \text{ kg}\) on average for males with obesity. As with female users, male users with obesity from Subgroup 3 lost a smaller amount of weight than in the other subgroups, but the difference was not as pronounced.

Exploratory post hoc gender comparisons of net changes in body weight from Q1 to Q4 showed that in Subgroups 1 and 2, female users with obesity lost more weight compared to their male counterparts. More specifically, weight loss \((\pm \text{SEM})\) was \(-1.9 (\pm 0.6)\) and \(-1.5 (\pm 0.5) \text{ kg}\) greater for females than male users in Subgroup 1 \((p = 0.002)\) and Subgroup 2 \((p = 0.003)\), respectively. No gender difference was observed for users with normal weight and overweight in those subgroups \((p > 0.025)\). Similarly, female and male users from Subgroup 3 did not differ in terms of weight loss, regardless of their BMI \((p > 0.013)\). Overall, 20% of users who had weight entries available achieved a clinically meaningful weight loss \((\geq 5\% \text{ loss from starting weight})\) from Q1 to Q4.

Because the greatest weight loss was observed in Subgroups 1 and 2 and due to the more consistent weight entries in those subgroups, monthly variations in body weight were examined for all users who entered their weight in the app at least once per month in exploratory analyses. These results are presented in Figure 2. The analyses revealed a significant interaction between month and BMI for female and male users, \(F(22, 2292) = 24.54, p < 0.001\), and \(F(22, 2695) = 15.76, p < 0.001\), respectively. Both female and male users with overweight and obesity tended to lose weight as the year went by \((all p < 0.001 \text{ for the simple effect of month})\). However, the decrease in weight tended to be smaller at the end of the year. While
there was no significant change in weight over time for female users with normal weight ($p = 0.018$), the weight of male users in this BMI category increased by a small yet significant amount from the beginning to the end of the year ($p < 0.001$).

### 3.6 Physical activity over time

Ninety-six percent (96%) of users recorded at least one physical activity in the app during the year. The average monthly physical activity is presented in Figure 3. The analyses revealed a significant main effect of month for both female and male users, $F(11, 8333) = 62.59, p < 0.001$, and $F(11, 8508) = 100.51, p < 0.001$, respectively. As illustrated in Figure 3, there was an increase in energy expended from the beginning of the calendar year to the summer months. Thereafter, physical activity decreased until the end of the year, returning to a similar level as observed in the early part of the year.

The effect of BMI was significant for both female and male users, $F(2, 4626) = 17.45, p < 0.001$, and $F(2, 4642) = 20.30, p < 0.001$. 

| Quarter of the year | Q1 | Q4 | Difference (kg) | Difference (%) |
|---------------------|----|----|-----------------|---------------|
| **Female users**    |    |    |                 |               |
| Subgroup 1: users who logged their weight at least once per week |    |    |                 |               |
| Normal ($n = 314$)  | 59.2 ± 0.6 | 59.4 ± 0.6 | 0.2 ± 0.3 | 0.3 ± 0.5 |
| Overweight ($n = 163$) | 72.2 ± 0.8 | 70.6 ± 0.8 | −1.6 ± 0.4 | −2.2 ± 0.6 |
| Obese ($n = 159$)    | 92.7 ± 0.8 | 86.7 ± 0.8 | −6.0 ± 0.4 | −6.5 ± 0.4 |
| Subgroup 2: users who logged their weight at least once per month |    |    |                 |               |
| Normal ($n = 352$)  | 60.1 ± 0.7 | 60.2 ± 0.7 | 0.1 ± 0.3 | 0.2 ± 0.5 |
| Overweight ($n = 219$) | 73.4 ± 0.9 | 72.0 ± 0.9 | −1.4 ± 0.4 | −1.9 ± 0.5 |
| Obese ($n = 249$)    | 98.5 ± 0.8 | 92.3 ± 0.8 | −6.2 ± 0.4 | −6.3 ± 0.4 |
| Subgroup 3: users who logged their weight at least once in Q1 and Q4 |    |    |                 |               |
| Normal ($n = 698$)  | 59.5 ± 0.4 | 59.8 ± 0.4 | 0.3 ± 0.2 | 0.5 ± 0.3 |
| Overweight ($n = 395$) | 73.3 ± 0.6 | 72.2 ± 0.6 | −1.1 ± 0.2 | −1.5 ± 0.3 |
| Obese ($n = 350$)    | 97.8 ± 0.6 | 94.8 ± 0.6 | −3.0 ± 0.2 | −3.1 ± 0.2 |

| **Male users**       |    |    |                 |               |
| Subgroup 1: users who logged their weight at least once per week |    |    |                 |               |
| Normal ($n = 239$)  | 73.8 ± 0.7 | 74.3 ± 0.7 | 0.5 ± 0.4 | 0.7 ± 0.5 |
| Overweight ($n = 295$) | 85.9 ± 0.6 | 85.5 ± 0.6 | −0.4 ± 0.3 | −0.5 ± 0.3 |
| Obese ($n = 201$)    | 109.5 ± 0.8 | 105.4 ± 0.8 | −4.1 ± 0.4 | −3.7 ± 0.4 |
| Subgroup 2: users who logged their weight at least once per month |    |    |                 |               |
| Normal ($n = 294$)  | 74.4 ± 0.7 | 74.8 ± 0.7 | 0.4 ± 0.3 | 0.5 ± 0.4 |
| Overweight ($n = 409$) | 86.1 ± 0.6 | 85.5 ± 0.6 | −0.6 ± 0.3 | −0.7 ± 0.3 |
| Obese ($n = 244$)    | 110.3 ± 0.8 | 105.5 ± 0.8 | −4.8 ± 0.4 | −4.4 ± 0.4 |
| Subgroup 3: users who logged their weight at least once in Q1 and Q4 |    |    |                 |               |
| Normal ($n = 310$)  | 74.4 ± 0.7 | 75.0 ± 0.7 | 0.6 ± 0.3 | 0.8 ± 0.4 |
| Overweight ($n = 537$) | 87.7 ± 0.6 | 87.5 ± 0.6 | −0.2 ± 0.2 | −0.2 ± 0.2 |
| Obese ($n = 380$)    | 112.2 ± 0.7 | 109.0 ± 0.7 | −3.2 ± 0.3 | −2.9 ± 0.3 |

Note: Mean value (±SEM) for each quarter of interest. The “Difference” columns indicate the mean change in weight between Q1 and Q4 (either in kg or in %) and the SEM. A negative value indicates that users lost weight on average from Q1 to Q4, whereas a positive value indicates that users gained weight on average. Values are adjusted for age, although this variable did not correlate with weight in any group (all $p ≥ 0.195$). The interaction between quarter and BMI group was significant in all Subgroups for both female and male users.

Abbreviations: Q, quarter; SEM, standard error of the mean.

*Next to a mean difference denotes a significant change with an alpha level of 0.01.
FIGURE 2  Mean body weight (kg) of female (A) and male (B) users who logged their weight at least once every month as a function of month and BMI category. All users from Subgroups 1 and 2 are considered for these analyses. Values are adjusted for age, although this variable did not correlate with weight for both female and male users (both \( p \geq 0.046 \)). Error bars represent the standard error of the mean

FIGURE 3  Average energy expended from physical activity (kcal/day) for female (A) and male (B) users as a function of month and BMI category. Values are adjusted for age, although this variable did not correlate with energy expended from activity for both female and male users (both \( p \geq 0.077 \)). Error bars represent the standard error of the mean

respectively. However, temporal changes in energy expended from physical activity were similar in all gender and BMI groups, as indicated by the absence of an interaction between month and BMI (all \( p \geq 0.238 \)). Pairwise comparisons showed that regardless of gender, users with obesity had smaller values of energy expended compared to users with normal weight and overweight (all \( p \geq 0.002 \)), but these two groups did not differ (all \( p \geq 0.013 \)). Overall, male users reported a higher level of physical activity over the year than females (mean energy expended [±SEM]: 236.0 [±3.2] kcal/day for female and 335.1 [±4.3] kcal/day for male users, \( p < 0.001 \)).

4  DISCUSSION

The goal of this study was to examine patterns of adherence to a caloric budget and body weight changes among users of a popular mHealth app who had daily caloric intake values available for one calendar year. The results support the hypothesis that adherence to a caloric budget is highest early on in a calendar year. However, although caloric intake was lowest in the first quarter for nearly all groups, only users with obesity met their caloric budget early in the year, while users with normal weight and overweight were over budget from the start. Mean caloric intake increased for all users from the first to second quarter, thereafter remaining relatively stable for users with normal weight and overweight, but further increased among users with obesity between the final two quarters.

It is notable that users with obesity remained closest to their caloric budget over the year compared to the other BMI groups, potentially reflecting their greater motivation for weight loss. This observation could also be partially explained by the fact that users with obesity had a higher caloric budget as the budget was dependent on a user’s weight. Despite their overall best adherence to caloric budget compared to other BMI groups, users with obesity displayed the most divergence from their budget over time. As self-regulation abilities and contextual influences are important determinants of behavior change,32 one potential explanation for this
observation is that users with obesity may have had a decrease in their self-regulation over time and/or became more susceptible to environmental food cues (particularly at the end of the year during various holidays). Indeed, higher BMI has been related to increased food cue reactivity and decreased inhibitory control, though these associations require further investigation. The results of the present study may reflect overall challenges with caloric restriction, which has been argued to be linked to the abundance of food options in the modern day food environment.

Although statistically significant, the observed variations in caloric intake over time were small in terms of the net number of calories consumed, likely reflecting the highly conscientious nature of individuals included in the analytical sample. However, the magnitude of caloric changes is relevant, because at a population level even small increases in caloric intake over time without compensation through expenditure can have significant impacts on weight gain. Previous studies of seasonal fluctuations in food consumption showed a downward rather than upward trend in caloric intake in the first months of a calendar year. In those investigations, however, participants were asked to maintain their weight or could not be actively engaged in weight loss. On the contrary, based on user reported goal weight, it is apparent that most app users in the sample were striving to lose weight. The general observation of lowest caloric intake at the beginning of the year for most users aligns with the common occurrence of weight loss goals that are set as New Year’s resolutions.

The observed results support the hypothesis that consistent self-monitoring of body weight in addition to calorie tracking is more effective for weight loss as users with more frequent weight entries lost the most weight. This observation is consistent with evidence from randomized-controlled trials of weight loss interventions showing the beneficial impact of frequent weight self-monitoring (for a review, see Zheng et al.). However, despite observing statistically significant changes, the observed average weight loss was not clinically meaningful and was in fact substantially lower than the desired weight loss. Altogether, the observations reflect the challenges around weight loss and need for strategies that support sustained adherence to self-monitoring, even among highly consistent and long-term mHealth app users. The effectiveness of mHealth apps could be enhanced by novel features that provide more targeted user feedback to support adherence. Nevertheless, although the average desired amount of weight loss by BMI category was reasonable, it remains possible that some users had unrealistic weight goals that resulted in demotivation and diminished adherence.

The observed variations in caloric intake by season and gender are important to discuss. As the complete sample of users ended the year with an average caloric intake that surpassed their caloric budget, it may be unexpected that some individuals still lost weight. However, users in general seemed to compensate with physical activity, particularly during the summer, which has also been reported in previous studies (for a review, see Tucker and Gilliland). Weight loss plateaued at the end of the year, which may be a result of the holiday season. Gender differences were apparent. Although male and female users with obesity in all subgroups had a statistically significant weight loss at the end of the year, only the female users with obesity who entered their body weight at least once per month had a clinically meaningful average weight loss. While both genders lost a smaller amount of weight in Subgroup 3 than in the other subgroups, this difference in weight loss across subgroups was more pronounced for female users. In addition, the deviation from caloric budget over time was generally smaller among females compared to male users, but physical activity was higher for male users.

The more stable caloric intake among female users in this analysis could be explained by the fact that women are generally considered to be more conscientious than men, or by a potentially greater motivation for weight loss due to higher body dissatisfaction. In this regard, despite the app being marketed for weight loss, there was a larger proportion of females (but not males) with normal weight than with overweight and obesity in the sample, which has also been reported by Chin et al. In general, users with normal weight did not have a significant net weight change, and the exploratory analysis of monthly variations in body weight showed a small weight gain among males from this BMI group. These results could reflect differences in motivations for app use (e.g., maintenance rather than weight loss) or limits on the possibility for weight loss. There is a clear need for more gender-specific research into longer-term weight loss/management efforts and the observations from this investigation require confirmation in separate studies.

There are several advantages to using data from consistent users of an mHealth app. These data enabled observation of self-monitoring in a naturalistic setting, which is a novel approach as most studies have been performed with homogeneous samples of predominantly white female participants. Food intake entries may be more complete in mHealth apps (in comparison with, e.g., paper diaries), which are considered convenient and time-efficient due to the large food databases available and could be less prone to underreporting. Indeed, reliability estimates were high even among groups previously known to underreport intake on dietary assessments (women and individuals with obesity). Moreover, besides from the Beltsville 1-year dietary intake study, no other known investigation has analyzed caloric intake data recorded daily for 1 year. The Beltsville study involved a high level of researcher contact to strive for accuracy and completion of daily food records for a small sample of participants. However, due to the nature of the data, it was not possible to verify completeness/accuracy of the caloric intake data in the current study. Future work could aim to assess the validity of mHealth app data by examining the correlations between values of caloric intake and body weight.

The present investigation is not without limitations. Data were only available for a single calendar year, thus it is not possible to determine whether the observed pattern is cyclical over multiple years. The location of users (United States and Canada) is also important to consider, as food intake and physical activity patterns may differ for other geographical locations. While the caloric budget is calculated by the app, users could manually increase or decrease it, but information was not available to assess the prevalence of manual
adjustments. Moreover, the proportion of app data that were self-entered versus synchronized with fitness trackers or smart scales is not known. Little sociodemographic information was available, which is common among studies using mHealth data given that minimal information is collected upon app sign up. Although the app is free and available to all smartphone users, it is not possible to infer the diversity of the present sample. This sample was comprised of substantially more male and older-aged individuals than previously observed among similar apps (where users were ~15 years younger and comprised of ~20% males). This is likely due to the present study’s focus on daily calorie tracking. Therefore, it must be acknowledged that the observations from this study are not generalizable to all mHealth app users, nor to the general population.  

5 | CONCLUSIONS

This investigation provides insight into the temporal dynamics of caloric intake and weight monitoring on weight loss outcomes. Among highly consistent users of an mHealth app, adherence to a caloric budget varied throughout a calendar year, with the most pronounced variation occurring early in the year. Given the importance of adherence to self-monitoring for weight loss, future studies that incorporate mHealth approaches should aim to identify factors that contribute to consistent adherence. Moreover, further uptake of app-derived food intake, physical activity, and body weight data in research is warranted, particularly to examine the validity and reliability compared to traditional measurement approaches.

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CONFLICT OF INTEREST

The authors have no conflict of interest to disclose. The company partner who provided the data for this investigation requested not to identify itself in the manuscript. None of the authors of this manuscript are employees or stockholders in the company.

AUTHOR CONTRIBUTIONS

Daiva E. Nielsen designed the study. Daiva E. Nielsen and Nathan Yang provided the data. Katherine Labonté analyzed data and wrote the manuscript. Bärbel Knäuper, Laurette Dubé, Nathan Yang, and Daiva E. Nielsen critically revised the manuscript. All authors approved the final version of the manuscript.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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