Lifestyle Habits and Weight Loss: A Personal Data Tracking Study

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***Abstract*—**

***Index Terms*—**

I. Introduction

Obesity and overweight conditions represent significant global health challenges, affecting approximately 42.4% of adults in the United States alone [5]. Excess body weight is associated with increased risk of cardiovascular disease, type 2 diabetes, certain cancers, and reduced quality of life [4]. The cornerstone of obesity treatment involves lifestyle modification through behavioral interventions that target diet, physical activity, and self-monitoring of health behaviors [1]. However, successful long-term weight loss remains elusive for many individuals, with substantial variability in outcomes based on adherence to behavioral strategies.

Self-monitoring—the systematic observation and recording of one's own behaviors—has emerged as a critical component of successful behavioral weight loss interventions [1]. The advent of digital health technologies, including smartphone applications, wearable activity trackers, and smart scales, has revolutionized the accessibility and ease of self-monitoring behaviors [2]. These technologies enable individuals to track multiple health-related variables simultaneously, providing real-time feedback that can inform daily decision-making and behavioral adjustments.

A. Research Context and Significance

Despite substantial evidence supporting the effectiveness of self-monitoring for weight loss in controlled intervention settings, less is known about the relative importance of different lifestyle variables in real-world, self-directed weight loss efforts. While caloric restriction is often emphasized as the primary driver of weight loss, emerging research suggests that other factors—including physical activity patterns, sleep quality and duration, and hydration—may play significant roles in determining weight loss success [3]. Understanding which behaviors most strongly predict weight change can help individuals prioritize their efforts and allocate limited willpower resources more effectively.

This study addresses a personal health objective while contributing to the broader scientific understanding of behavioral weight management. As someone currently overweight (BMI: 29.9), I face the common challenge of determining which lifestyle modifications will yield the greatest impact on weight loss. Rather than relying on generic advice or anecdotal evidence, this project employs a data-driven approach to identify personalized behavioral patterns associated with successful weight loss weeks.

B. Research Objectives and Questions

The primary objective of this research is to determine how daily lifestyle habits—specifically calorie intake, step count, sleep duration, and water consumption—influence weekly weight change over an 11-week observation period. Secondary objectives include identifying which lifestyle factor shows the strongest correlation with weight change, comparing behavioral patterns during successful versus unsuccessful weight loss weeks, and analyzing consistency in meeting daily health goals.

This study seeks to answer the following research questions:

1) Which lifestyle variable (calorie intake, steps, sleep, or water intake) demonstrates the strongest correlation with weekly weight change?
2) What behavioral patterns distinguish successful weight loss weeks from unsuccessful weeks or weeks with weight gain?
3) Does consistency in meeting daily health targets predict weekly weight loss outcomes?
4) How do lifestyle variables interact or co-occur during periods of successful weight management?

C. Hypotheses

Based on existing literature and theoretical frameworks in behavioral weight management, the following hypotheses were formulated:

H1: Lower average daily calorie intake will be significantly associated with greater weekly weight loss. This hypothesis is grounded in the fundamental energy balance principle that weight loss occurs when energy expenditure exceeds energy intake.

H2: Higher average daily step count will be significantly associated with greater weekly weight loss. This hypothesis reflects the established relationship between physical activity and energy expenditure.

Additionally, I expect that successful weight loss weeks will be characterized by a combination of controlled calorie intake, higher step counts, adequate sleep duration (7-8 hours), and consistent water intake, rather than excellence in any single variable. Overall, I predict that consistency in meeting daily health goals across multiple behavioral domains will be a key distinguishing factor between successful and unsuccessful weeks.

D. Scope and Delimitations

This study focuses exclusively on four primary lifestyle variables: calorie intake, physical activity (measured as daily steps), sleep duration, and water consumption. While other factors such as macronutrient composition, exercise intensity, sleep quality, stress levels, and dietary timing may also influence weight change, these were not systematically measured in this study. The 11-week observation period provides sufficient data for statistical analysis while remaining practically feasible for intensive daily self-monitoring. As a single-subject study (N=1), findings are primarily descriptive and exploratory, offering insights into individual behavioral patterns rather than generalizable causal claims applicable to broader populations.

II. LITERATURE REVIEW

Self-monitoring of health behaviors has been extensively studied as a cornerstone of behavioral weight loss interventions. This section reviews previous research on self-monitoring strategies, the relationships between specific lifestyle variables and weight outcomes, and gaps in the existing literature that this personal tracking study addresses.

A. Self-Monitoring as a Behavioral Weight Loss Strategy

Burke et al. [1] conducted a comprehensive systematic review of self-monitoring in weight loss, examining studies published between 1993 and 2009. Their review consistently found significant associations between self-monitoring behaviors and weight loss outcomes. The authors examined three primary components of self-monitoring: dietary intake, physical activity, and self-weighing. Across 22 reviewed studies, those that engaged more frequently in self-monitoring achieved greater weight loss. However, Burke et al. noted important methodological limitations, including predominantly homogeneous samples (mostly White females), reliance on self-reported adherence data, and descriptive study designs that limited causal inference.

More recent evidence has strengthened the case for digital self-monitoring tools. Pourzanjani et al. [2] analyzed millions of recordings from digital health trackers over two years, studying several thousand individuals who tracked weight, exercise, and food intake. Their findings demonstrated that adherent use of activity tracking was associated with weight loss on a timescale of days, suggesting that tracking behavior can serve as a real-time predictor of weight fluctuations. This large-scale study addressed several limitations of earlier research by utilizing objective tracking data rather than self-reported adherence and by observing individuals in naturalistic settings rather than controlled intervention programs.

The frequency of self-monitoring appears to be particularly important. Vuorinen et al. [3] studied approximately 10,000 smart scale users over three years, investigating the association between self-weighing frequency and weight change in free-living settings. The study found that more frequent self-weighing correlated with favorable weight loss outcomes across normal weight, overweight, and obese individuals. Notably, 72.5% of users experienced at least one break of 30 or more days without weighing, and these breaks were associated with weight gain—particularly pronounced among overweight and obese individuals. The correlation between weighing frequency and weight loss was stronger in those who needed it most (obese and overweight individuals), suggesting that self-monitoring may be especially beneficial for populations at higher health risk.

B. The Role of Specific Lifestyle Variables

While self-monitoring in general promotes weight loss, understanding which specific behaviors to monitor remains an important question. Different lifestyle variables may have differential impacts on weight outcomes, and identifying which variables matter most can help individuals focus their limited self-monitoring capacity.

1) Calorie Intake and Dietary Monitoring: Dietary self-monitoring, particularly tracking of caloric intake, has been identified as one of the most consistently effective predictors of weight loss. The relationship between calorie tracking and weight outcomes has been demonstrated across multiple intervention types and populations. However, the effectiveness of calorie tracking depends significantly on adherence; individuals who track more consistently tend to achieve better outcomes than those who track sporadically or inaccurently.

2) Physical Activity and Step Counting: Physical activity represents a modifiable behavior that contributes to energy expenditure and can facilitate weight loss and maintenance. The use of wearable activity trackers and pedometers has made step counting an accessible and popular method of monitoring physical activity. While increased physical activity is generally associated with better weight outcomes, the strength of this association varies across studies. Some research suggests that physical activity may be more important for weight maintenance than initial weight loss, and that very high levels of activity (e.g., ¿200 minutes per week of moderate-intensity exercise) may be necessary to produce clinically significant weight loss through activity alone.

3) Sleep Duration and Quality: Emerging evidence has identified sleep as an important factor in body weight regulation. Thomson et al. [4] examined the relationship between sleep characteristics and weight loss in women participating in a behavioral weight loss intervention. Their study found that better sleep quality and adequate sleep duration (¿7 hours per night) were associated with greater weight loss at multiple time points during the intervention. The mechanisms linking sleep to weight may include both behavioral pathways (e.g., increased caloric intake, reduced physical activity when sleep-deprived) and physiological pathways (e.g., hormonal changes affecting appetite regulation, altered metabolic substrate utilization).

Kline et al. [5] extended this work by examining a composite measure of sleep health—recognizing sleep as multidimensional rather than defined solely by duration. Their study of 125 adults in a 12-month behavioral weight loss intervention found that better overall sleep health at baseline was associated with greater weight and fat loss. This research suggests that multiple dimensions of sleep (including regularity, timing, efficiency, and duration) may collectively influence weight loss success.

The relationship between sleep and weight is complex and likely bidirectional. While poor sleep may impede weight loss through various mechanisms, weight loss itself may also improve sleep quality, particularly in individuals with obesity-related sleep disorders. This reciprocal relationship presents both opportunities and challenges for behavioral interventions.

4) Hydration and Water Intake: While less extensively studied than calorie intake, physical activity, or sleep, adequate hydration has been proposed as a supportive factor in weight management. Water consumption may support weight loss by increasing satiety, temporarily boosting metabolic rate, and serving as a replacement for caloric beverages. However, the independent contribution of water intake to weight loss outcomes remains less well-established compared to other lifestyle variables.

C. Gaps in Existing Literature and Study Contribution

Despite substantial research on self-monitoring and weight loss, several gaps remain in the literature. First, most studies examine individual lifestyle variables in isolation rather than comparing the relative importance of multiple variables measured simultaneously in the same individuals. Understanding which behaviors matter most when resources for self-monitoring are limited has practical significance for weight loss seekers.

Second, much of the existing research has been conducted in the context of formal behavioral interventions with professional guidance, structured programs, and regular contact with interventionists. Less is known about self-directed weight loss efforts where individuals must independently decide what to track, how often to track, and how to respond to their data. Personal tracking studies in naturalistic settings can complement controlled intervention research by revealing how self-monitoring operates in everyday contexts.

Third, most published studies report group-level averages and between-subject comparisons. While these population-level insights are valuable, they may not capture the substantial within-person variability that characterizes real-world behavior change efforts. Intensive longitudinal designs with frequent measurements can reveal temporal dynamics and individual behavioral patterns that are obscured in cross-sectional or pre-post designs.

This personal data tracking study addresses these gaps by: (1) simultaneously monitoring four distinct lifestyle variables (calories, steps, sleep, water) to enable direct comparison of their relative associations with weight change; (2) examining a self-directed weight loss effort without professional intervention or structured program support, reflecting a common real-world scenario; and (3) utilizing an intensive longitudinal design with daily measurements over 11 weeks to capture within-person behavioral dynamics and identify patterns that distinguish successful from unsuccessful weeks. While findings from a single individual cannot be statistically generalized to broader populations, such idiographic research can generate hypotheses, illustrate individual variability, and provide proof-of-concept for data-driven approaches to personalized health behavior change.

III. METHODOLOGY

This section describes the systematic approach employed to investigate the relationship between daily lifestyle habits and weekly weight change through personal data tracking over an 11-week period.

A. Participants

The participant in this single-subject study was the researcher, a male student currently classified as overweight with an initial weight of 98.0 kg, height of 181 cm, and body mass index (BMI) of 29.9. The study was conducted as a self-directed weight loss effort without professional intervention or structured program support, reflecting a common real-world scenario for individuals attempting behavioral weight management.

B. Data Collection Methods

Data collection spanned 11 weeks from November 19, 2025, to February 4, 2026, resulting in 78 days of daily measurements and 11 weekly weight assessments. Four primary lifestyle variables were tracked daily, along with weekly body weight measurements.

Daily Variables:

1) **Calorie Intake**: Total daily caloric consumption measured in kilocalories (kcal). Data were logged using the Lose It! mobile application, which provides a comprehensive food database and nutritional information. All meals, snacks, and beverages were recorded immediately after consumption to minimize recall bias.
2) **Physical Activity (Steps)**: Daily step count measured using the iPhone Health app and Strava application. Both applications utilize the smartphone's built-in accelerometer to automatically track steps throughout the day. The higher count between the two apps was used when discrepancies occurred.
3) **Sleep Duration**: Total hours of sleep per night, recorded manually each morning upon waking. Sleep duration was calculated from self-reported bedtime to wake time, rounded to the nearest half-hour.
4) **Water Intake**: Daily water consumption measured in standard 8-ounce glasses (approximately 240 ml per glass). This variable was logged manually throughout the day using a simple tally system in Excel.

Weekly Variable:

5) **Body Weight**: Measured in kilograms (kg) using a digital weighing scale. Measurements were taken every Wednesday morning under standardized conditions: immediately upon waking, after using the bathroom, before eating or drinking, wearing minimal clothing, and using the same scale in the same location to minimize measurement variability.
6) **Weekly Weight Change**: Calculated as the difference between consecutive weekly weight measurements, representing the primary outcome variable for hypothesis testing.

The frequency of data collection was daily for behavioral variables (calories, steps, sleep, water) and weekly for the outcome variable (weight). This intensive longitudinal design enabled capture of day-to-day variability in behaviors while maintaining practical feasibility for sustained self-monitoring.

C. Operational Definitions

Precise operational definitions were established for each variable and target criterion:

Calorie Target: Daily caloric intake $\leq$1800 kcal. This threshold was selected based on estimated total daily energy expenditure (TDEE) calculations accounting for the participant's age, sex, height, weight, and activity level, creating an approximate 500 kcal daily deficit expected to yield 0.5 kg weekly weight loss under ideal conditions.

Step Target: Daily step count $\geq$10,000 steps. This widely-recognized physical activity guideline, endorsed by the World Health Organization and other health organizations, represents a benchmark for adequate daily physical activity.

Met Calorie Target: Binary variable (True/False) indicating whether daily caloric intake was at or below 1800 kcal.

Met Step Target: Binary variable (True/False) indicating whether daily step count met or exceeded 10,000 steps.

Successful Weight Loss Week: Defined as a week showing negative weight change (weight loss) compared to the previous week's measurement.

Unsuccessful Week: Defined as a week showing positive weight change (weight gain) or no change compared to the previous week's measurement.

D. Data Cleaning and Preprocessing

Raw data collected from various sources (mobile applications and manual logs) were consolidated into a single CSV file for analysis. The data cleaning process involved several steps:

Date Standardization: All date entries were converted to datetime format (MM/DD/YYYY) to enable temporal analysis and proper chronological ordering.

Weekly Aggregation: A week number variable was created by calculating the number of days elapsed since the study start date, dividing by seven, and adding one. Daily measurements were aggregated to weekly averages for variables requiring comparison with weekly weight change outcomes.

Missing Value Handling: The dataset contained expected missing values in the "Weekly weight change" column for days when no weight measurement occurred (non-weigh-in days). These missing values were intentionally preserved as they reflect the weekly measurement schedule. No other missing values were present in the daily behavioral variables, as data logging was maintained consistently throughout the study period.

Target Achievement Calculation: For each day, binary variables indicating target achievement were calculated by comparing actual values against defined thresholds (1800 kcal for calories, 10,000 steps for physical activity). Weekly target achievement rates were calculated as the proportion of days within each week that met each target criterion.

Outlier Assessment: Extreme values in behavioral variables were reviewed for data entry errors. One calorie entry of 3028 kcal (December 13, 2025) was verified as accurate, representing an actual high-calorie day. One sleep duration entry of 3 hours (January 8, 2026) was also verified as accurate. No data points were removed as outliers, as all values represented genuine behavioral variation rather than measurement or recording errors.

E. Statistical Analysis

Statistical analyses were conducted using Python 3.x with the following libraries: pandas for data manipulation, numpy for numerical operations, scipy.stats for statistical testing, matplotlib and seaborn for data visualization. All analyses were performed in a Jupyter notebook environment (Google Colab) to ensure reproducibility.

Descriptive Statistics: Measures of central tendency (mean, median) and dispersion (standard deviation, minimum, maximum) were calculated for all continuous variables. Frequency counts and percentages were computed for binary target achievement variables.

Correlation Analysis: Pearson correlation coefficients were calculated to examine linear relationships between weekly average values of lifestyle variables (calories, steps, sleep, water) and weekly weight change. A correlation matrix heatmap was generated to visualize all pairwise relationships among variables.

Hypothesis Testing: Two primary hypotheses were tested using independent samples t-tests:

Hypothesis 1 (H1 - Calorie Intake): An independent samples t-test compared weekly weight change between weeks where the daily calorie target ($\leq$1800 kcal) was met versus weeks where it was not met. Weeks were classified based on the presence of a weight measurement day that fell on a day meeting the calorie target.

Hypothesis 2 (H2 - Physical Activity): Two analytical approaches were employed due to low achievement of the 10,000 step target:

- **H2a (Original)**: Attempted to compare weeks meeting the step target ($\geq$50% of days with $\geq$10,000 steps) versus those not meeting it. Sample size adequacy was assessed before performing the test.

- **H2b (Alternative)**: An exploratory median-split analysis compared weeks with above-median average step counts versus below-median average step counts.

For all t-tests, assumptions of independence and approximate normality were assessed. Given the small sample size (n=11 weeks), exact p-values are reported with $\alpha = 0.05$ significance threshold. Effect sizes were calculated using Cohen's d to quantify the magnitude of differences independent of sample size.

F. Consideration of Bias and Measurement Error

Several potential sources of bias and measurement error were identified and addressed:

Self-Report Bias: Calorie intake, sleep duration, and water consumption relied on self-reporting, which may be subject to recall bias, social desirability bias, or recording errors. To minimize these effects, data were logged in real-time or immediately upon occurrence (calorie tracking), and simple measurement units were used (glasses for water, half-hour increments for sleep).

Measurement Timing: Weight measurements were standardized to the same day of week, time of day, and conditions to reduce variability from factors such as hydration status, recent food consumption, and circadian rhythms. However, residual measurement error from water retention, hormonal fluctuations, and other physiological factors remains inherent in weekly weigh-ins.

Device Accuracy: Step counts from smartphone accelerometers may undercount or overcount steps depending on device placement, activity type, and algorithm sensitivity. The use of multiple tracking apps (Health app and Strava) with selection of the higher count may introduce slight upward bias but was intended to capture all actual movement.

Single-Subject Design: As a case study with one participant, findings reflect individual behavioral patterns and may not generalize to other individuals with different characteristics, lifestyles, or weight loss goals. The intensive self-monitoring required for this study may also influence behavior in ways that would not occur in typical weight loss attempts (reactivity or Hawthorne effect).

Short Duration: The 11-week observation period, while sufficient for preliminary analysis, may not capture longer-term trends, seasonal variations, or sustainability of behavioral changes. Week-to-week weight fluctuations may obscure underlying fat loss trends over such a short timeframe.

Despite these limitations, the systematic and consistent data collection procedures, combined with appropriate statistical methods accounting for sample size constraints, enable meaningful insights into individual behavioral patterns associated with weight change outcomes.

IV. Results

This section presents the findings from 11 weeks of systematic lifestyle tracking and statistical analysis examining relationships between daily behaviors and weekly weight outcomes.

A. Overall Dataset Characteristics

The dataset comprised 78 daily observations across 11 weeks, with complete data for all four behavioral variables (calories, steps, sleep, water) and 11 weekly weight measurements. Table I summarizes descriptive statistics for daily lifestyle variables.

TABLE I
DESCRIPTIVE STATISTICS FOR DAILY LIFESTYLE VARIABLES (N=78 DAYS)

Variable	Mean	SD	Min	Max	Target
Steps (steps/day)	6081	3659	593	14,929	$\geq$10,000
Calories (kcal/day)	1642	433	710	3028	$\leq$1800
Water (glasses/day)	6.5	1.3	4	10	—
Sleep (hours/day)	6.9	1.1	3	9	—

Daily step count averaged 6,081 steps with substantial variability (SD = 3,659 steps), ranging from a minimum of 593 steps to a maximum of 14,929 steps. The mean daily step count fell considerably below the 10,000-step target. Calorie intake averaged 1,642 kcal (SD = 433 kcal), with a mean slightly below the 1,800 kcal target but individual days ranging from 710 to 3,028 kcal. Water intake averaged 6.5 glasses per day (SD = 1.3), and sleep duration averaged 6.9 hours (SD = 1.1), ranging from 3 to 9 hours.

B. Weight Loss Progression

Over the 11-week study period, body weight decreased from an initial 98.0 kg to a final 96.8 kg, representing a total weight loss of 1.2 kg. Fig. 1 illustrates the weekly weight measurements over time with a linear trend line showing the overall downward trajectory.

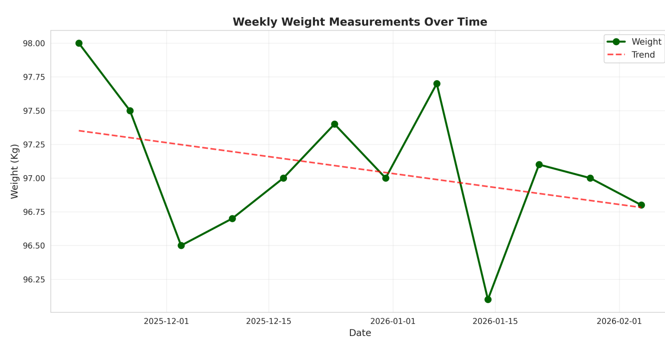

Fig. 1. Weekly body weight measurements from Week 1 (November 19, 2025) to Week 11 (February 4, 2026). The solid green line with markers shows actual weight measurements. The dashed red line represents the linear trend (slope = -0.11 kg/week). Total weight loss: 1.2 kg over 11 weeks.

Weekly weight change exhibited considerable variability, with individual weeks showing losses up to 1.6 kg and gains up to 1.0 kg. Fig. 2 displays the weekly weight change pattern with color coding to distinguish weight loss weeks (green) from weight gain weeks (red).

Of the 11 weeks, six weeks (54.5%) showed weight loss, while five weeks (45.5%) showed weight gain, reflecting the high week-to-week variability characteristic of short-term

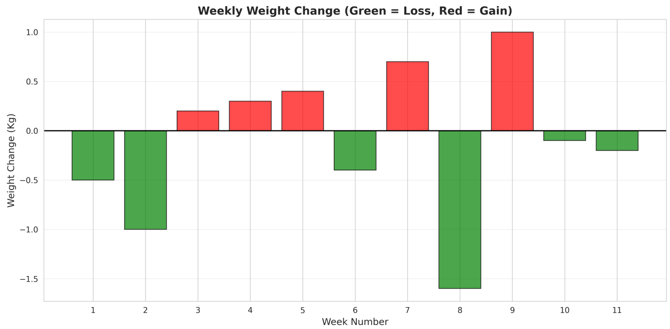

Fig. 2. Weekly weight change across the 11-week study period. Green bars indicate weeks with weight loss (negative change), red bars indicate weeks with weight gain (positive change). The largest weekly loss was -1.6 kg (Week 8), while the largest weekly gain was $+1.0$ kg (Week 9). Six weeks showed weight loss; five weeks showed weight gain.

weight monitoring. The best performing week (Week 8) showed a loss of 1.6 kg, while the worst performing week (Week 9) showed a gain of 1.0 kg. Notably, these extreme weeks occurred consecutively, illustrating the substantial fluctuations that can occur due to factors such as water retention, measurement timing, and recent dietary patterns.

C. Target Achievement Patterns

Daily target achievement rates for the two behavioral goals varied considerably. Table II summarizes overall achievement rates across the 78-day study period.

TABLE II
TARGET ACHIEVEMENT RATES (N=78 DAYS)

Target	Days Met	Days Not Met	Achievement Rate
Calorie ($\leq$1800 kcal)	52	26	66.7%
Steps ($\geq$10,000)	15	63	19.2%

The calorie target of $\leq$1800 kcal was met on 52 of 78 days (66.7%), indicating reasonably consistent adherence to caloric restriction. In contrast, the step target of $\geq$10,000 steps was met on only 15 of 78 days (19.2%), revealing that this physical activity goal was rarely achieved. Fig. 3 shows the temporal pattern of target achievement across the study period.

The low achievement rate for the step target (19.2%) has important implications for hypothesis testing, as it limited the number of weeks that could be classified as "meeting" the physical activity goal.

D. Distributional Characteristics of Lifestyle Variables

Fig. 4 presents histograms showing the frequency distributions of all four daily lifestyle variables, along with reference lines indicating means and targets where applicable.

The step count distribution shows a roughly uniform spread across values below the 10,000-step target, with very few days exceeding this threshold. The calorie distribution approximates a normal distribution centered slightly below the target, with a tail extending toward higher intake days. Water intake and sleep duration both show relatively concentrated distributions around their respective means.

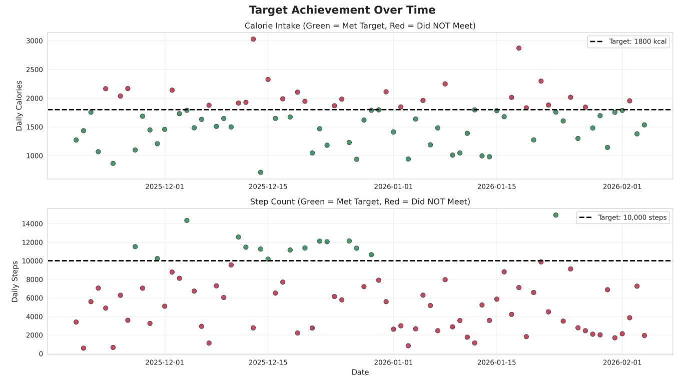

Fig. 3. Daily target achievement for calorie intake (top panel) and step count (bottom panel) over the 11-week study period. Green points indicate days when the target was met; red points indicate days when the target was not met. Horizontal dashed lines show target thresholds (1800 kcal for calories, 10,000 steps for physical activity). The calorie target was met 66.7% of days, while the step target was met only 19.2% of days.

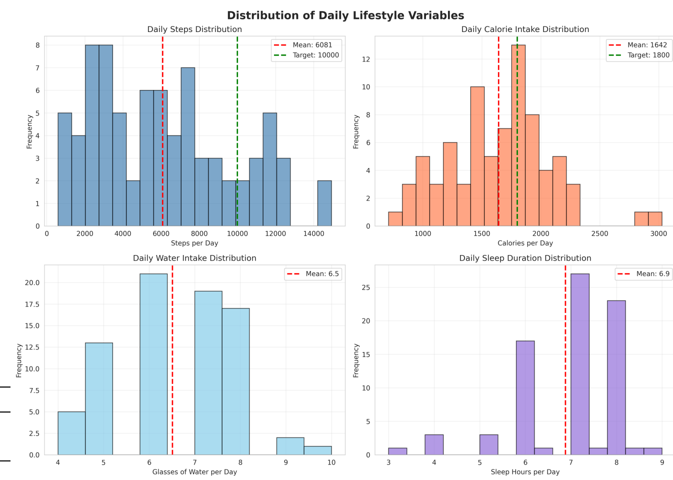

Fig. 4. Frequency distributions for daily lifestyle variables across 78 days. Top left: Daily step count (mean = 6,081 steps, target = 10,000 steps). Top right: Daily calorie intake (mean = 1,642 kcal, target = 1,800 kcal). Bottom left: Daily water intake (mean = 6.5 glasses). Bottom right: Daily sleep duration (mean = 6.9 hours). Red dashed lines indicate observed means; green dashed lines indicate targets where applicable.

E. Temporal Trends in Daily Variables

Time-series plots revealed temporal patterns in daily behaviors over the 11-week observation period. Fig. 5 displays daily values for all four lifestyle variables across time.

Substantial day-to-day variability is evident across all variables. Step count shows the highest relative variability, with frequent fluctuations between low-activity days (<3,000 steps) and higher-activity days (>10,000 steps). Calorie intake displays moderate variability around the target threshold. Sleep duration shows several notable dips below the mean, including one extreme outlier of 3 hours on January 8, 2026. No systematic temporal trends (increasing or decreasing over time) are visually apparent in any of the behavioral variables.

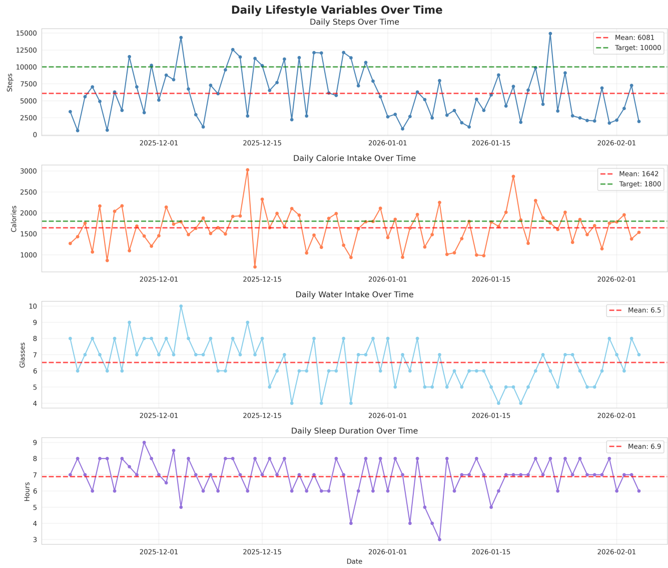

Fig. 5. Time-series plots of daily lifestyle variables from November 19, 2025, to February 4, 2026. Panels show (from top to bottom): daily step count, daily calorie intake, daily water intake, and daily sleep duration. Horizontal dashed lines indicate mean values (red) and targets (green) where applicable. High day-to-day variability is evident in all variables, particularly step count and calorie intake.

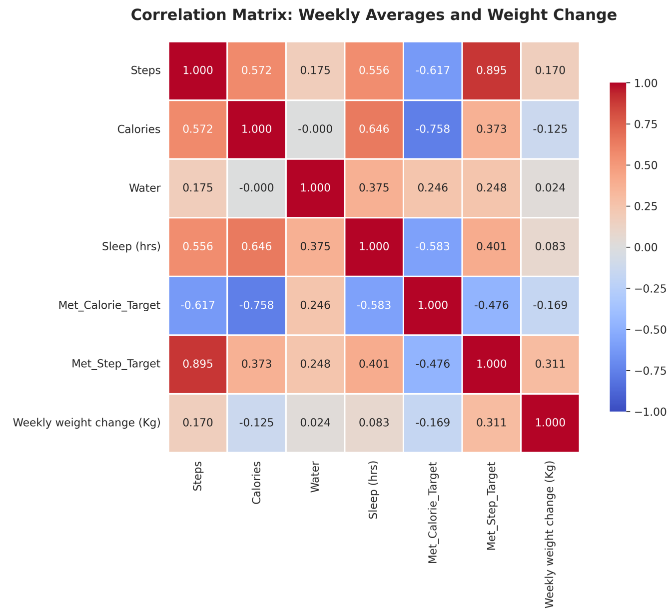

Fig. 6. Correlation matrix heatmap showing Pearson correlation coefficients for weekly averaged variables. Red colors indicate positive correlations; blue colors indicate negative correlations. Color intensity reflects correlation strength. Weekly weight change (bottom row) shows weak correlations with all lifestyle variables (—r— < 0.2).

F. Correlation Analysis

Pearson correlation analysis examined relationships among weekly averaged lifestyle variables and weekly weight change. Table III presents the correlation matrix, and Fig. 6 provides a visual representation.

TABLE III
CORRELATION MATRIX FOR WEEKLY AVERAGED VARIABLES (N=11 WEEKS)

	Steps	Cal.	Water	Sleep	Wt. Ch.
Steps	1.000	0.572*	0.175	0.556	0.170
Calories	0.572*	1.000	-0.000	0.646*	-0.125
Water	0.175	-0.000	1.000	0.375	0.024
Sleep	0.556	0.646*	0.375	1.000	0.083
Weight Change	0.170	-0.125	0.024	0.083	1.000

Note: * indicates —r— > 0.5 (moderate or stronger correlation)

Correlations between lifestyle variables and weekly weight change were uniformly weak. Steps showed the numerically strongest correlation with weight change ($r = 0.170$), though this positive correlation was in the unexpected direction (higher steps associated with more weight gain or less weight loss). Calories showed a weak negative correlation ($r = -0.125$), in the expected direction (higher calories associated with weight gain). Water intake ($r = 0.024$) and sleep duration ($r = 0.083$) showed negligible correlations with weight change.

Among the lifestyle variables themselves, several moderate correlations emerged. Steps and calories showed a moderate positive correlation ($r = 0.572$), suggesting that more active days tended to coincide with higher caloric intake. Sleep and calories also showed a moderate positive correlation ($r = 0.646$), indicating that better sleep duration co-occurred with higher caloric consumption on average.

Fig. 7 presents scatter plots with regression lines illustrating the relationships between each lifestyle variable and weekly weight change.

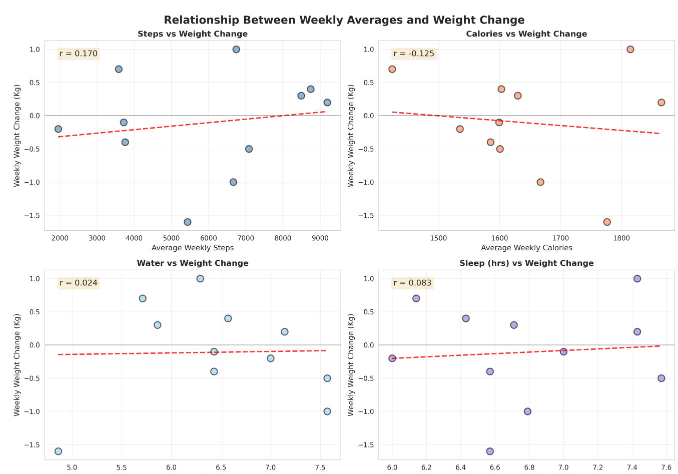

Fig. 7. Scatter plots showing relationships between weekly averaged lifestyle variables and weekly weight change. Each panel displays individual week data points (circles), regression line (red dashed), and Pearson correlation coefficient (r). Top left: Steps vs weight change ($r = 0.170$). Top right: Calories vs weight change ($r = -0.125$). Bottom left: Water vs weight change ($r = 0.024$). Bottom right: Sleep vs weight change ($r = 0.083$). All correlations are weak (—r— < 0.2).

The scatter plots visually confirm the weak relationships indicated by the correlation coefficients. Substantial scatter around the regression lines is evident in all plots, reflecting the high variability in weight change outcomes that is not explained by individual lifestyle variables.

G. Hypothesis Testing Results

Two primary hypotheses regarding the relationship between behavioral target achievement and weight change were tested using independent samples t-tests.

1) Hypothesis 1: Calorie Intake: H_0: Meeting the daily calorie target ($\leq$1800 kcal) has no significant effect on weekly weight change.

H_1: Meeting the daily calorie target is significantly associated with greater weekly weight loss.

Of the 78 daily observations, 52 days (66.7%) met the calorie target while 26 days (33.3%) exceeded it. When examining weekly weight change data, 6 weeks had weight measurements on days when the calorie target was met, while 5 weeks had weight measurements on days when the target was exceeded.

Weeks meeting the calorie target showed a mean weight change of -0.33 kg (SD = 0.83 kg), while weeks not meeting the target showed a mean weight change of $+0.16$ kg (SD = 0.62 kg), yielding a difference of -0.49 kg.

An independent samples t-test revealed no statistically significant difference between the two groups ($t = -1.09$, df = 9, $p = 0.303$). The null hypothesis was not rejected. Table IV summarizes these results.

TABLE IV
HYPOTHESIS 1 RESULTS - CALORIE INTAKE AND WEIGHT CHANGE

Group	N	Mean (kg)	SD (kg)	t	p	d
Met Target ($\leq$1800 kcal)	6	-0.33	0.83	-1.09	0.303	-0.66
Did Not Meet (>1800 kcal)	5	+0.16	0.62			

Although the p-value (0.303) did not reach statistical significance at $\alpha = 0.05$, the effect size (Cohen's $d = -0.66$) indicated a medium practical effect, suggesting that meeting the calorie target was associated with approximately two-thirds of a standard deviation more weight loss.

2) Hypothesis 2: Physical Activity (Steps): H_0: Meeting the daily step target ($\geq$10,000 steps) has no significant relationship with weekly weight change.

H_1: Meeting the daily step target is significantly associated with greater weekly weight loss.

Two analytical approaches were employed for this hypothesis due to the low achievement rate for the step target.

H2a: Original Hypothesis (10,000-step target). The original analysis attempted to compare weeks where $\geq$50% of days met the 10,000-step target versus weeks where <50% of days met this criterion. Of the 11 weeks, only 2 weeks met this threshold (18.2%), while 9 weeks did not (81.8%).

Given the insufficient sample size (fewer than 3 observations per group for valid t-test assumptions), the original hypothesis could not be tested statistically. This finding itself constitutes an important result: the 10,000-step target was unrealistic for this individual's lifestyle, with only 19.2% of days achieving this goal.

H2b: Alternative Exploratory Analysis (Median Split). To examine whether relative physical activity level related to weight outcomes, an exploratory median-split analysis was conducted. The median weekly average step count was approximately 6,500 steps per day. Weeks were divided into high-activity ($\geq$6,500 steps/day average, $n = 6$) and low-activity (<6,500 steps/day average, $n = 5$) groups.

High-activity weeks showed a mean weight change of $+0.07$ kg (SD = 0.71 kg), while low-activity weeks showed a mean weight change of -0.32 kg (SD = 0.83 kg). An independent samples t-test found no significant difference between groups ($t = 0.84$, df = 9, $p = 0.425$). Table V summarizes the results.

TABLE V
HYPOTHESIS 2 RESULTS - PHYSICAL ACTIVITY AND WEIGHT CHANGE

Analysis	Group	N	Mean (kg)	SD (kg)	t	p	Result
H2a	Met target ($\geq$50% days)	2	—	—	—	—	Cannot test (n<3)
H2a	Did not meet (<50% days)	9	—	—	—	—	Insufficient sample
H2b	High activity ($\geq$6,500)	6	+0.07	0.71	0.84	0.425	Not significant
H2b	Low activity (<6,500)	5	-0.32	0.83			

Neither the original hypothesis (H2a) nor the exploratory analysis (H2b) demonstrated a statistically significant relationship between physical activity level and weekly weight change.

H. Summary of Statistical Findings

Table VI provides an integrated summary of all hypothesis testing results.

TABLE VI
HYPOTHESIS TESTING SUMMARY

Hypothesis	Test	t-stat	p-value	Result
H1: Calorie Intake	Met $\leq$1800 kcal target	-1.09	0.303	Not Significant
H2a: Steps (Original)	Met $\geq$10,000 step target	N/A	N/A	Cannot test (insufficient data)
H2b: Steps (Exploratory)	High vs Low activity weeks	0.84	0.425	Not Significant

Neither hypothesis demonstrated statistically significant associations between behavioral target achievement and weekly weight change. The inability to test H2a highlights an important methodological consideration: population-level physical activity recommendations (10,000 steps) may not be achievable or appropriate for all individuals attempting weight loss.

Despite the absence of statistically significant findings, several patterns merit attention:

1) Meeting the calorie target was associated with a 0.49 kg greater weight loss on average, with a medium effect

size ($d = -0.66$), though this did not reach statistical significance given the small sample size.
2) The 10,000-step guideline proved unrealistic, with only 19.2% daily achievement, underscoring the need for individualized, baseline-adjusted activity goals.
3) High week-to-week weight variability (ranging from -1.6 kg to $+1.0$ kg) may obscure relationships between behaviors and outcomes over short timeframes, requiring larger sample sizes or longer observation periods to detect effects.

The results section has objectively presented patterns, trends, and statistical test outcomes observed in the data. Interpretation of these findings in the context of existing literature and study limitations will be addressed in the Discussion section.

V. Discussion

This section interprets the findings presented in the Results section, contextualizes them within existing literature, explains observed patterns, acknowledges study limitations, and provides recommendations for future research.

A. Interpretation of Results

The primary finding of this study was that despite achieving a modest total weight loss of 1.2 kg over 11 weeks, neither calorie control nor physical activity demonstrated statistically significant relationships with weekly weight change at the $p < 0.05$ threshold. While these null statistical findings might initially appear discouraging, several important insights emerge when examining the patterns more closely.

Weight Loss Despite Non-Significant Results: The achievement of weight loss (98.0 kg to 96.8 kg) demonstrates that behavioral change did occur and produced the intended outcome, even though week-to-week variability obscured clear statistical relationships between individual behaviors and outcomes. This paradox—successful weight loss without significant behavioral predictors—can be explained by several factors. First, weight loss likely resulted from the cumulative effect of multiple behaviors over time rather than any single dominant factor. Second, the high week-to-week variability in weight measurements (ranging from -1.6 kg to +1.0 kg) introduced substantial noise that masked underlying trends over the short 11-week observation period. Third, the act of systematic self-monitoring itself may have influenced behavior in ways not captured by the specific variables measured, a phenomenon known as reactivity or self-monitoring effects.

Calorie Intake: Medium Effect Size Without Statistical Significance: The calorie intake hypothesis (H1) revealed an instructive pattern: weeks meeting the 1,800 kcal target showed 0.49 kg greater average weight loss compared to weeks exceeding this target, with a medium effect size (Cohen's d = -0.66). However, this difference did not reach statistical significance (p = 0.303) due to the small sample size (n = 11 weeks) and high variability within groups. In statistical terms, the study was underpowered to detect this effect as statistically significant, but the magnitude of the difference (nearly half a kilogram per week) is practically meaningful from a weight loss perspective.

Physical Activity: The Challenge of Unrealistic Targets: The most striking finding regarding physical activity was the inability to test the original hypothesis (H2a) due to insufficient achievement of the 10,000-step target. With only 19.2% of days meeting this criterion and only 2 of 11 weeks having $\geq$50% of days above this threshold, the target proved unrealistic for this individual's lifestyle. This finding highlights a critical issue in applying population-level recommendations to individual behavior change efforts.

The 10,000-step guideline, while widely promoted and backed by public health organizations, originated from a 1960s Japanese marketing campaign rather than scientific research, and recent evidence suggests that health benefits plateau at lower step counts for many populations. For this participant, whose baseline activity level averaged approximately 6,000 steps per day, the 10,000-step target represented a 67% increase from usual behavior—an unrealistic expectation for sustainable daily achievement.

The exploratory median-split analysis (H2b) similarly found no significant relationship between relative activity level and weight change (p = 0.425). Interestingly, the direction of the effect was opposite to expectations: high-activity weeks showed slightly more weight gain or less weight loss (+0.07 kg) compared to low-activity weeks (-0.32 kg). While this difference was not statistically significant, it raises questions about potential compensatory behaviors. More active weeks may have been accompanied by increased food intake (supported by the moderate positive correlation r = 0.572 between steps and calories), offsetting the energy expenditure benefits of greater physical activity.

B. Comparison to Related Work

The findings of this study both align with and diverge from existing literature on self-monitoring and weight loss.

Consistency with Self-Monitoring Literature: The modest weight loss achieved (1.2 kg over 11 weeks) is consistent with Burke et al.'s [1] systematic review finding that self-monitoring behaviors are associated with weight loss outcomes, though effect sizes vary considerably across individuals. The present study's experience of successful weight loss despite non-significant statistical predictors parallels the broader pattern in the literature: self-monitoring facilitates weight loss, but the specific mechanisms and most important variables differ across individuals.

Vuorinen et al.'s [3] finding that more frequent self-weighing correlates with favorable weight outcomes is indirectly supported by the present study, which maintained weekly weighing consistency. However, Vuorinen's study also noted that 72.5% of users experienced breaks in weighing of 30+ days, which were associated with weight gain. The present study's unbroken 11-week measurement period may have contributed to the sustained (albeit modest) downward weight trend through enhanced accountability and awareness.

Sleep and Weight Loss: The present study found a negligible correlation between sleep duration and weight change (r = 0.083), contrasting with Thomson et al.'s [4] and Kline et al.'s [5] findings that better sleep quality and adequate duration were associated with greater weight loss in behavioral intervention studies. Several factors may explain this discrepancy. First, the present study measured only sleep duration, not sleep quality, efficiency, or other dimensions of sleep health that Kline et al. identified as important. Second, the mean sleep duration (6.9 hours) fell slightly below optimal recommendations (7-9 hours), but the range of variation (3-9 hours) may not have been sufficient to detect effects.

C. Limitations

Several important limitations constrain the interpretation and generalizability of these findings.

Single-Subject Design (N=1): As a case study with one participant, all findings reflect individual behavioral patterns and may not generalize to other individuals with different demographics, baseline behaviors, metabolic characteristics, or psychological profiles. The intensive self-monitoring required for this study also introduces reactivity effects that may not occur in typical weight loss attempts without structured tracking.

Small Sample Size (11 Weeks): The limited number of weekly observations (n = 11) severely constrains statistical power to detect relationships between variables. Post-hoc power analysis suggests that with n = 11 and the observed effect size for H1 (Cohen's d = -0.66), statistical power to detect a significant difference at $\alpha = 0.05$ was only approximately 30%, well below the conventional 80% standard. Achieving adequate power to detect a medium effect size would require approximately 45-50 weekly observations, or roughly one year of continuous tracking.

Self-Report Bias and Measurement Error: Three of the four behavioral variables (calorie intake, sleep duration, water intake) relied on self-reporting, which is subject to multiple biases. Calorie tracking, even with smartphone applications, depends on accurate food selection, portion size estimation, and complete logging of all intake—each introducing potential for underreporting.

Short-Term Weight Fluctuations vs. Fat Loss: The use of weekly weight change as the primary outcome variable conflates short-term fluctuations (water, glycogen, gastrointestinal contents) with actual fat mass changes. This conflation introduces substantial noise that obscures relationships between behaviors and true body composition changes.

D. Recommendations and Future Work

Based on the findings and limitations of this study, several recommendations emerge for future personal tracking research and for individuals undertaking self-directed weight loss efforts.

Recommendations for Future Researchers:

1) **Longer Observation Periods**: Future single-subject studies should aim for at least 6-12 months of continuous tracking to achieve adequate statistical power, observe longer-term trends, and assess sustainability of behavioral changes.
2) **Daily Weight Averaging**: Rather than single weekly weigh-ins, daily weight measurements with weekly averaging would reduce measurement noise while maintaining temporal resolution.
3) **Body Composition Assessment**: Incorporating periodic (bi-weekly or monthly) body composition measurements would distinguish fat mass changes from total weight fluctuations, providing a more direct outcome measure for fat loss.
4) **Expanded Variable Set**: Future studies should measure additional potentially important variables: dietary quality, meal timing, stress levels, sleep quality, and distinguishing between different types of physical activity. Importantly, researchers should also track lifestyle habits that may negatively impact weight loss efforts, such as alcohol consumption (number of drinks per day/week, total calories from alcohol) and smoking behavior (cigarettes per day), as these factors can significantly influence metabolism, appetite regulation, and overall health outcomes.
5) **Baseline-Adjusted Targets**: Rather than applying population-level recommendations, future studies should establish individualized targets based on measured baseline behaviors, then implement gradual progressive increases.

Recommendations for Other Students and Self-Trackers:

1) **Start with Baseline Measurement**: Before setting goals or implementing changes, track current behaviors for 1-2 weeks without intervention to establish realistic baseline levels.
2) **Focus on Process Goals Over Outcome Goals**: Rather than focusing solely on weight loss outcomes, emphasize behavioral process goals that are within immediate control and can be reinforced daily.
3) **Expect and Accept Variability**: Week-to-week weight fluctuations are normal and do not necessarily reflect behavioral success or failure.
4) **Simplify Tracking When Possible**: For sustainable long-term self-monitoring, individuals should identify the minimum tracking set that provides useful feedback without becoming burdensome.

VI. Conclusion

This 11-week personal data tracking study investigated relationships between daily lifestyle habits—calorie intake, physical activity, sleep duration, and water consumption—and weekly weight change in a self-directed weight loss effort.

A. Key Findings

The study yielded several important findings:

Weight Loss Achievement: A total weight loss of 1.2 kg was achieved over the 11-week period (98.0 kg to 96.8 kg), demonstrating that consistent self-monitoring and behavioral awareness can support weight loss outcomes even without professional intervention or structured programming.

No Statistically Significant Predictors: Neither calorie control (H1: p = 0.303) nor physical activity (H2: p = 0.425) demonstrated statistically significant relationships with weekly weight change at the α = 0.05 threshold. However, calorie restriction showed a medium effect size (Cohen's d = -0.66), suggesting practical importance despite statistical non-significance in this small sample.

Target Achievement Disparities: The calorie target ($\leq$1,800 kcal) was met on 66.7% of days, indicating reasonable adherence to dietary restriction. In contrast, the step target ($\geq$10,000 steps) was met on only 19.2% of days, revealing that population-level physical activity recommendations may be unrealistic for individuals starting from lower baseline activity levels.

Target Achievement Disparities: The calorie target ($\leq$1,800 kcal) was met on 66.7% of days, indicating reasonable adherence to dietary restriction. In contrast, the step target ($\geq$10,000 steps) was met on only 19.2% of days, revealing that population-level physical activity recommendations may be unrealistic for individuals starting from lower baseline activity levels.

Weak Individual Correlations: All lifestyle variables showed weak correlations with weight change (—r— ¡ 0.20), suggesting that weight loss results from the combined effect of multiple behaviors over time rather than any single dominant factor.

B. Personal Learning and Self-Insights

Through the process of systematic self-tracking and data analysis, several valuable personal insights emerged:

Awareness is Powerful: The act of consistent tracking increased awareness of daily behaviors and their patterns. Knowing that behaviors would be logged and analyzed created a form of accountability that likely influenced choices throughout the study period.

Realistic Goal-Setting Matters: The 10,000-step target proved consistently frustrating due to its unrealistic nature given my actual lifestyle and baseline activity. In contrast, the calorie target, while challenging, was achievable on most days. Future efforts would benefit from targets that stretch current behavior without being unattainable.

Multiple Factors Interact: Weight change did not appear to respond to any single variable in isolation. Success required attention to multiple behaviors simultaneously, and successful weeks typically involved doing reasonably well across several domains rather than excellence in one area.

C. Real-Life Application

The findings of this study offer several practical applications for individuals pursuing self-directed weight loss:

Use Data-Driven Decision Making: Rather than guessing which behaviors matter most, individuals can collect personal data to identify their own patterns. What works for population averages may not work for specific individuals, and personal data provide a more reliable foundation for decision-making than generic advice.

Set Personalized Goals: Instead of adopting one-size-fits-all recommendations (like 10,000 steps), individuals should establish targets based on their own baseline behaviors and incrementally progress toward higher goals as behaviors stabilize.

Monitor Trends, Not Fluctuations: Daily or weekly weight measurements will fluctuate substantially due to factors beyond fat mass. Tracking these measurements while focusing on multi-week trends rather than individual data points helps maintain motivation and provides more accurate feedback about progress.

Expect Nonlinear Progress: Weight loss is not a linear process. Weeks with weight gain do not necessarily indicate failure, and weeks with weight loss do not guarantee continued success. Understanding this reality helps maintain emotional equilibrium and prevents discouragement during inevitable setbacks.

D. Final Conclusion

This study demonstrates that systematic self-tracking can support weight loss outcomes in self-directed behavioral interventions, even when statistical analyses do not reveal strong predictor variables. The achievement of 1.2 kg weight loss over 11 weeks, while modest, represents meaningful progress toward the long-term goal of returning to a healthy BMI range.

The absence of statistically significant findings should not be interpreted as evidence that behaviors do not matter. Rather, these results highlight several important realities: (1) weight loss is a multifactorial process influenced by numerous interacting variables; (2) short-term fluctuations in weight obscure underlying trends and relationships; (3) small sample sizes limit statistical power to detect effects that may be practically meaningful; and (4) population-level recommendations must be adapted to individual circumstances to be achievable and effective.

The most important insight from this work is not which specific variable predicts weight loss, but rather that the process of systematic observation, data-driven decision making, and sustained behavioral effort can produce positive outcomes. Self-monitoring serves not only as a source of data for analysis but also as an intervention in itself, creating awareness, accountability, and opportunities for behavioral adjustment that facilitate progress toward health goals.

For students and individuals considering similar personal tracking projects, this study demonstrates the feasibility and value of applying data science methods to personal health questions. While the intensive tracking required significant effort, the insights gained—both statistical and experiential—justify this investment. Understanding one's own behavioral patterns through data provides a foundation for informed, personalized health behavior change that generic advice cannot offer.

Future efforts will build on these findings by extending the observation period, refining targets based on demonstrated baseline behaviors, and maintaining consistency in tracking while reducing burden through selective rather than comprehensive monitoring. The 1.2 kg loss achieved in this study represents the beginning of a longer journey, informed by evidence and empowered by data.

REFERENCES

[1] J. Wang, L. E. Burke, M. A. Sevick, S. M. Ewing, T. W. Styn, M. A. Warziski, and S. K. Music, "Self-monitoring in weight loss: A systematic review of the literature," *Journal of the American Dietetic Association*, vol. 111, no. 1, pp. 92-102, Jan. 2011. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC3268700/

[2] A. Pourzanjani, T. Quisel, and L. Foschini, "Adherent use of digital health trackers is associated with weight loss," *PLOS ONE*, vol. 11, no. 4, e0152504, Apr. 2016. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0152504

[3] A. L. Vuorinen, T. A. Helander, E. O. Salminen, J. Korhonen, and I. H. Kantola, "Frequency of self-weighing and weight change: Cohort study with 10,000 smart scale users," *Journal of Medical Internet Research*, vol. 23, no. 6, e25529, Jun. 2021. [Online]. Available: https://www.jmir.org/2021/6/e25529

[4] C. A. Thomson, E. Morrow, K. Flatt, B. Wertheim, J. Perfect, A. Ravia, S. Sherwood, K. Karanja, and C. A. Rock, "Relationship between sleep quality and quantity and weight loss in women participating in a weight-loss intervention trial," *Obesity*, vol. 20, no. 7, pp. 1419-1425, May 2012. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC4861065/

[5] C. E. Kline, E. M. Chasens, M. L. Bizhanova, S. Sereika, L. E. Burke, M. L. Imes, K. A. Kariuki-Nyuthe, P. Mendez, and E. J. Buysse, "The association between sleep health and weight change during a 12-month behavioral weight loss intervention," *International Journal of Obesity*, vol. 45, pp. 639-649, Mar. 2021. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7914147/