Exploring Self-Regulated Break Behavior and Its Impact on Post-Break Focus: A Self-Tracking Observational Study

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***Abstract*—Breaks are integral to sustaining attention and productivity, yet the dynamics of self-regulated, naturally occurring breaks in real-world contexts remain underexplored. This single-subject observational study analyzed 71 self-tracked breaks to investigate factors influencing whether breaks exceeded their planned durations (overshoot) and how overshoot affected post-break focus. Variables included break triggers, break activities, task difficulty, and time of day. Exploratory analysis revealed that mental fatigue and hunger were common triggers, while eating and lying down were frequent break activities. Statistical testing using Kruskal–Wallis and Mann–Whitney U tests indicated that task anxiety significantly predicted overshoot duration, whereas break activity, task difficulty, and time of day did not. Overshooting planned breaks was associated with lower post-break focus, suggesting that maintaining planned break durations supports effective cognitive re-engagement. These results highlight the critical role of emotional triggers, particularly anxiety, in prolonging self-regulated breaks and provide actionable insights for optimizing focus and productivity in everyday work and study routines.**

***Index Terms*—time management, break behavior, self-regulation, self-track, productivity, overshoot**

I. Introduction

Daily habits, including how we manage work, rest, and transitions between tasks, play a critical role in personal productivity and cognitive functioning. Breaks, ranging from very short micro-breaks to longer rest periods, are a common human response to sustained mental effort. Evidence from cognitive science suggests that breaks can help restore energy, reduce fatigue, and support sustained attention [1].

While prior studies have examined structured break schedules in laboratory and classroom settings, less is known about naturally occurring, self-regulated break behavior in real-world contexts. For example, Biwer et al. (2023) compared self-regulated breaks to Pomodoro-style scheduled breaks and found that self-chosen breaks were often longer and associated with higher fatigue and lower concentration, highlighting the need to understand break behavior in self-regulated learning [2]. Similarly, Smits et al. (2025) investigated self-regulated, Pomodoro, and Flowtime break techniques and emphasized that research on authentic, self-chosen break patterns is limited [3].

Although structured techniques like Pomodoro or Flowtime have been shown to improve productivity, most people do not consistently use these methods in everyday life. By examining naturally occurring self-regulated breaks, this study aims to understand real-world patterns of break behavior and their relationship with post-break focus, providing insights that can complement or inform the use of structured productivity techniques. Understanding these patterns is particularly relevant for managing daily study sessions, work tasks, and other focused activities where attention and energy fluctuate over time.

This study analyzes personal break behavior using a self-logged dataset, collected in real time, to explore factors that influence whether breaks exceed their planned duration and whether such overshoots are associated with changes in post-break focus. By studying real-world, naturally occurring patterns, this research aims to provide practical insights for improving self-regulation, maintaining focus, and optimizing productivity in daily life.

The study is guided by the following research questions:

1) How do break triggers, break activities, task difficulty, and time of day relate to overshooting planned break durations?
2) Do breaks that exceed their planned durations lead to better, worse, or unchanged post-break focus?

To support statistical testing, the following null and alternative hypotheses were formulated.

- H_{01}: There is no statistically significant difference in overshoot duration across different break triggers.
- H_{11}: There is a statistically significant difference in overshoot duration across different break triggers.
- H_{02}: There is no statistically significant difference in overshoot duration across different break activities.
- H_{12}: There is a statistically significant difference in overshoot duration across different break activities.
- H_{03}: There is no statistically significant difference in overshoot duration across levels of task difficulty.
- H_{13}: There is a statistically significant difference in overshoot duration across levels of task difficulty.

- H_{04}: There is no statistically significant difference in overshoot duration across different time-of-day periods.
- H_{14}: There is a statistically significant difference in overshoot duration across different time-of-day periods.
- H_{05}: There is no significant difference in post-break focus between overshooting and on-time breaks.
- H_{15}: There is a significant difference in post-break focus between overshooting and on-time breaks.

Through this personalized analysis, the study seeks to contribute to a deeper understanding of how break behavior can be optimized in everyday productivity routines, offering actionable insights for managing focus and energy during work or study sessions.

II. Review of Related Literature

A. Effects of Breaks on Cognitive Performance

Research consistently shows that breaks can mitigate fatigue and support sustained cognitive performance. Albulescu et al. (2022), in a systematic review and meta-analysis of micro-break interventions, found that short breaks can improve well-being and have small but positive effects on performance, particularly for tasks requiring sustained attention [1]. Their findings suggest that periodic disengagement from a task may help restore cognitive resources, especially under prolonged mental effort.

However, the effectiveness of breaks depends on multiple factors, including break duration, activity type, and task demands. The variability observed across studies indicates that breaks are not universally beneficial in all forms, highlighting the need to understand contextual influences on break outcomes.

B. Self-Regulated Break Taking and Effort Regulation

While structured break techniques such as the Pomodoro method prescribe fixed work–rest cycles, many individuals regulate breaks based on internal cues such as fatigue or boredom. Biwer et al. (2023) examined effort regulation by comparing self-regulated breaks with systematic (Pomodoro-style) breaks. They found that participants in self-regulated conditions tended to take longer breaks and experienced higher fatigue and lower concentration compared to those following structured schedules [2].

These findings suggest that self-regulated break-taking may not always optimize cognitive performance, particularly when individuals rely solely on subjective feelings to determine timing and duration. The study highlights the importance of examining naturally occurring break behavior to better understand how effort regulation unfolds in real-world contexts.

Similarly, Smits et al. (2025) compared self-regulated, Pomodoro, and Flowtime break techniques in authentic student study sessions. Although differences were observed in fatigue and motivational patterns, overall productivity did not significantly differ across techniques [3]. Importantly, the authors noted that research on break-taking in authentic, self-regulated environments remains limited, reinforcing the need for further investigation of real-world break behavior.

C. Research Gap

Existing literature has largely focused on comparing structured and self-regulated break techniques under controlled conditions. While these studies provide valuable insights into effort regulation and fatigue, less is known about how break duration naturally unfolds in everyday contexts and how deviations from intended break length may influence subsequent focus.

In particular, the phenomenon of breaks exceeding their planned duration has received limited direct investigation. Understanding the factors associated with such overshoots and their relationship with post-break focus may provide practical insights into personal productivity and self-regulation.

III. Methodology

This study employed a single-subject self-tracking observational design to investigate behavioral factors affecting productivity breaks. Event-level data were systematically recorded during actual study sessions and analyzed using statistical techniques to determine patterns in break duration and post-break focus. The methodological procedures used in the study are presented in this section.

A. Participants

The participant in this study was the researcher, a 22-year-old Bachelor of Science in Computer Science (BSCS) student. The participant regularly engages in academic study sessions involving computer-based tasks and programming activities. No additional personal or sensitive demographic information was collected, as the study focused only on observable study and break behavior.

B. Data Collection Methods

Data were collected through manual logging of each study break using an Excel spreadsheet. The following variables were recorded for every break:

TABLE I
RECORDED STUDY BREAK VARIABLES

Variable	Description
Date	The day the study session occurred.
Time	The time the break started.
Task Before Break	The activity being performed prior to taking a break.
Task Difficulty	Self-reported complexity of the task (Low / Medium / High).
Planned Break (min)	Intended duration of the break in minutes.
Break Trigger	Reason for taking the break (e.g., task anxiety, hunger, phone notification).
Break Activity	Action performed during the break (e.g., resting, walking, phone use).
Actual Break (min)	Actual duration of the break in minutes.
Returned on Time?	Indicator if the break ended as planned.
Feeling After Break	Self-reported focus or cognitive state after returning.
Note	Any additional observations.

Breaks were logged in real time to minimize recall bias, resulting in an event-level dataset suitable for analysis. While not every day had a recorded break, multiple breaks were often logged per day, providing a rich dataset for examining patterns of break behavior and post-break focus.

C. Operational Definitions

Some variables in this study were derived from the raw break-log dataset to facilitate analysis. In particular, the main outcome variable, Productivity Break Overshoot, and its categorical counterpart, Overshoot Flag, were computed from the difference between actual and planned break durations. All other variables, such as break trigger, activity, task difficulty, post-break focus, and time of day, were either directly recorded or encoded from self-reports.

1) Overshoot: Defined as the difference between the actual break duration and the planned break duration, measured in minutes:

$$\text{Overshoot} = \text{Actual Break (min)} - \text{Planned Break (min)} \quad (1)$$

If the result is greater than 0, the break exceeded the intended time. This variable served as the main dependent measure of the study.

2) Overshoot Flag: A categorical indicator derived from the overshoot measure:

- Yes: Overshoot > 0
- No: Overshoot ≤ 0

This variable was used for categorical statistical tests.

3) Break Trigger: The categorical reason for taking a break, representing the psychological or physical cause of disengagement. Examples include:

- Task anxiety
- Hunger
- Headache
- Phone notification
- Habit/autopilot
- Emergency
- Mental fatigue

4) Break Activity: The action performed during the break. Examples include:

- Phone use
- Eating
- Resting
- Walking
- Other personal activities

This variable was used to test whether the type of break activity influences overshoot.

5) Task Difficulty: Self-reported complexity of the task performed before the break, encoded numerically as:

- Low = 1
- Medium = 2
- High = 3

This variable was used to examine whether the complexity of a task influences overshoot.

6) Feeling After Break (Post-Break Focus): Self-reported cognitive readiness after returning from a break, encoded as:

- More tired = -1
- More distracted = 0
- Neutral = 1
- More focused = 2

This variable served as a measure of post-break cognitive recovery.

7) Time of Day: Derived from the break timestamp and categorized into behavioral periods:

- Early Morning ($<$6 AM)
- Morning (6–12)
- Afternoon (12–18)
- Evening/Night ($>$18)

This allowed grouping breaks into meaningful time-of-day periods for analysis.

D. Data Preparation

Data preparation was conducted through a series of systematic steps to ensure consistency, accuracy, and suitability for analysis.

1) Data Cleaning: The dataset was examined for missing values and duplicate entries. The Note column contained a substantial number of missing values, which was expected as it represented optional comments and did not affect the core variables used in the analysis. Duplicate records were checked and addressed as necessary. Frequency counts were performed on categorical variables such as Break Trigger, Break Activity, and Task Difficulty to verify consistent labeling and identify any inconsistencies.

2) Type Conversion: The Time column was converted into datetime format to enable temporal categorization and analysis. The Actual Break (min) column contained a non-numeric entry ("500+"), which was converted to the numeric value 500 to allow for quantitative calculations.

3) Encoding of Ordinal Variables: Ordinal categorical variables were converted into numeric representations to support statistical analysis:

- Task Difficulty: Low (1), Medium (2), High (3)
- Post-Break Focus State: More tired (-1), More distracted (0), Neutral (1), More focused (2)

4) Feature Engineering: Additional variables were derived to support the research objectives:

- Overshoot: Calculated as the difference between Actual Break (minutes) and Planned Break (minutes)
- Overshoot Flag: A binary variable indicating whether a break exceeded its planned duration
- Time of Day: Categorized based on recorded time into Early Morning, Morning, Afternoon, and Evening/Night

E. Statistical Analysis

1) Data Visualization and Exploratory Analysis: Before formal statistical testing, the dataset was visually explored to understand overall patterns, distributions, and relationships. This step also guided the choice of appropriate statistical tests.

2) Overall Patterns and Distributions:

- Countplot (Seaborn): Displayed frequencies of categorical variables such as Break Triggers, Break Activities, Overshoot Flag (Yes/No), and Feeling After Break.
- Histplot (Seaborn): Showed the distribution of Overshoot Minutes, revealing a skewed distribution with long-tail outliers.

3) Factor-wise Comparisons:

- Barplot (Seaborn): Compared median Overshoot Minutes across categories (Break Trigger, Activity, Task Difficulty, Time of Day) to detect which groups tend to produce longer overshoots.
- Stacked Bar (Pandas): Visualized the percentage of breaks exceeding planned durations per category, highlighting variations in overshoot likelihood.

4) Factor Combinations and Correlations:

- Heatmap (Seaborn): Showed median Overshoot Minutes for combinations of Break Trigger and Break Activity, identifying which pairings led to especially long breaks.
- Regplot with jitter (Seaborn): Examined the relationship between Task Difficulty and Overshoot to visually assess monotonic trends before formal correlation analysis.

5) Statistical Comparisons and Focus:

- Boxplot (Seaborn): Displayed distributions of Overshoot Minutes across Break Triggers and highlighted differences in Post-Break Focus between On-Time and Overshoot breaks. Significance markers indicated statistically meaningful differences.

6) Temporal Trends:

- Lineplot (Seaborn): Tracked daily median Overshoot Minutes across the study period to reveal trends and variability in break behavior over time.

F. Statistical Tests

After exploratory visualization, formal statistical tests were conducted to confirm observed patterns in overshoot behavior and post-break focus.

1) Tests for Group Differences:

a) Kruskal–Wallis H-test: The Kruskal–Wallis H test was applied to determine whether overshoot duration differed across categorical variables, including Break Trigger, Break Activity, Task Difficulty, and Time of Day. Exploratory plots revealed highly skewed overshoot data with extreme outliers and some categories with relatively small sample sizes. ANOVA assumes normally distributed data and sufficient sample sizes; extreme values can disproportionately influence the mean. Kruskal–Wallis ranks the data rather than using raw values [4], treating extreme values as the highest ranks rather than inflating averages. This makes it robust for non-normal distributions and small samples.

H-statistic formula:

$$H = \frac{12}{N(N+1)} \Sigma\left(\frac{R_i^2}{n_i}\right) - 3(N+1)$$

Fig. 1. Formula for calculating the Kruskal–Wallis H statistic to test for differences across multiple groups.

Where:

- N = total number of observations
- k = number of groups
- R_i = sum of ranks for group i
- n_i = number of observations in group i

Interpretation: Higher H-statistics indicate greater differences between group ranks. A p-value < 0.05 suggests that at least one group differs significantly from the others.

b) Mann–Whitney U Test (Post-hoc): When Kruskal–Wallis indicated significant differences, Mann–Whitney U tests were used for pairwise comparisons to determine which specific groups differed [5]. This test is robust to skewed data, extreme values, and small sample sizes. Unlike t-tests, it compares general tendencies in ranks rather than raw means, enabling meaningful pairwise comparisons (e.g., Hunger vs. Boredom triggers or On-Time vs. Overshoot groups).

Formula:

$$U_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2$$

Fig. 2. Formula for calculating the Mann–Whitney U statistic used for pairwise comparisons between groups.

Where:

- n_1, n_2 = sample sizes of the two groups
- R_1, R_2 = sum of ranks for each group

Interpretation: The U-statistic reflects the number of times a value from one group outranks a value from another. A corresponding low p-value indicates statistically significant differences.

c) Effect Size – Eta-squared (η^2): To complement the significance testing, η^2 (eta-squared) was computed to quantify the proportion of total variance in Overshoot Minutes that is explained by Break Triggers. This measure provides insight into the practical importance of the effects, beyond mere statistical significance.

Formula:

$$\eta^2 = \frac{H - k + 1}{N - k}$$

Fig. 3. Formula for computing eta-squared to quantify effect size in Kruskal–Wallis analysis.

Where: H = Kruskal–Wallis H statistic, k = number of groups, N = total sample size.

Interpretation: 0.01 = small, 0.06 = medium, 0.14 = large effect.

2) *Tests for Association:*

a) Spearman Rank-Order Correlation: Spearman correlation was used to examine monotonic relationships between ordinal or numeric variables [6], such as Task Difficulty and Overshoot duration. Ranking the data prior to calculation avoids assumptions of linearity and normality, making it appropriate for ordinal variables and skewed continuous data.

Formula:

$$\rho = 1 - \frac{6\Sigma\, d_i^2}{n(n^2 - 1)}$$

Fig. 4. Formula for calculating Spearman's rank correlation coefficient for ordinal or non-normal data.

Where: ρ = Spearman's rank correlation coefficient, d_i = difference between ranks, n = number of observations.

Interpretation:

- $\rho = +1$: perfect positive monotonic relationship
- $\rho = -1$: perfect negative monotonic relationship
- $\rho = 0$: no consistent monotonic relationship

3) *Focus Outcome Testing:*

a) Mann–Whitney U Test: A Mann–Whitney U test compared ranked Post-Break Focus scores between On-Time and Overshoot breaks. This test is appropriate for ordinal outcome variables and small, skewed groups.

Interpretation: A low p-value (< 0.05) indicates exceeding planned breaks significantly affects post-break focus.

b) Effect Size – Cliff's δ: Cliff's δ was calculated to assess the magnitude of the difference in Post-Break Focus between On-Time and Overshoot breaks. Unlike Cohen's d, Cliff's δ is a non-parametric effect size that does not assume normal distributions and is appropriate for ordinal or skewed data.

Formula for Cliff's δ:

$$\delta = \frac{\sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathrm{sgn}(X_{1i} - X_{2j})}{n_1 \cdot n_2}$$

Fig. 5. Formula for calculating Cliff's δ, representing the probability that a randomly selected value from one group is higher than a randomly selected value from the other group.

Where:

- n_1, n_2 = sample sizes of the two groups
- X_1, X_2 = observations in group 1 and group 2
- δ = proportion of pairs where $X_1 > X_2$ minus proportion of pairs where $X_1 < X_2$

Interpretation:

- $|\delta| < 0.147$ = negligible effect
- $0.147 \leq |\delta| < 0.33$ = small effect
- $0.33 \leq |\delta| < 0.474$ = medium effect
- $|\delta| \geq 0.474$ = large effect

4) *Linear Mixed-Effects Modeling (LMM):*

Some days may have multiple breaks, and factors like mood, fatigue, or workload on a given day could influence all breaks. This means the breaks are not independent, and one unusually long or short break might be related to other breaks on the same day. Ignoring this could lead standard tests to overstate the effect of factors such as Break Trigger or Task Difficulty. To account for this, a Linear Mixed-Effects Model was fitted, including Date as a random effect to handle clustering of breaks within the same day while still estimating the effect of predictors (fixed effects) on overshoot duration. For robustness and to reduce the influence of extreme values, overshoot duration was log-transformed prior to modeling. This approach helps mitigate bias from multiple entries per day and provides more accurate estimates of the factors affecting overshoot minutes.

Formula:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + u_j + \epsilon_{ij}$$

Fig. 6. Formula for the Linear Mixed-Effects Model predicting Overshoot Minutes while accounting for day-level clustering.

Where:

- Y_{ij} = outcome variable (overshoot minutes)
- β_0 = fixed intercept
- $\beta_1, \beta_2, \ldots$ = fixed-effect coefficients
- $X_{1ij}, X_{2ij}, \ldots$ = predictors
- $u_j \sim N(0, \sigma_u^2)$ = random effect for Date
- $\epsilon_{ij} \sim N(0, \sigma^2)$ = residual error

Interpretation of Coefficients: Indicates predicted increase or decrease in overshoot minutes associated with each factor, adjusted for day-level effects.

IV. Results

A. Exploratory Data Analysis

1) *Overall Dataset Characteristics:*

TABLE II
SUMMARY STATISTICS OF STUDY BREAKS

Metric	Planned Break (min)	Actual Break (min)	Overshoot (min)	Post-Break Focus (Encoded)
Mean	24.65	94.76	70.11	0.86
Median	15.00	39.00	12.00	1.00
Std. Deviation	21.48	145.57	135.76	1.00

a) Overall Descriptive Statistics (N = 71): Table 2 presents the descriptive statistics for planned break duration, actual break duration, overshoot time, and encoded post-break focus across the 71 recorded break sessions.

The planned break duration had a mean of 24.65 minutes, a median of 15.00 minutes, and a standard deviation of 21.48 minutes, reflecting variation in planned break lengths.

The actual break duration showed a mean of 94.76 minutes, a median of 39.00 minutes, and a standard deviation of 145.57 minutes, indicating a broad range of recorded durations.

Overshoot time recorded a mean of 70.11 minutes, a median of 12.00 minutes, and a standard deviation of 135.76 minutes. The encoded post-break focus score had a mean of 0.86, a median of 1.00, and a standard deviation of 1.00.

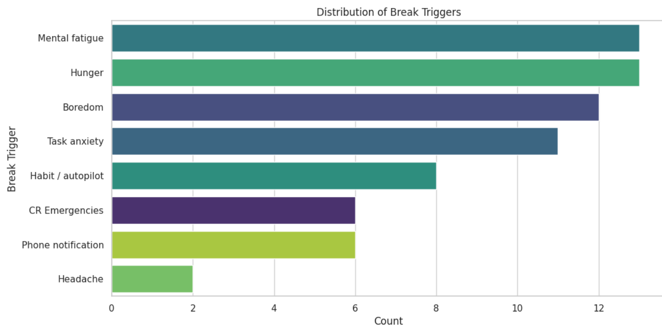

Fig. 7. Frequency of break triggers recorded across 71 break sessions.

b) Distribution of Break Triggers: Figure 8 shows the distribution of reported break triggers in the dataset. Mental fatigue and hunger were the most frequently recorded triggers, each occurring 13 times. Boredom (12) and task anxiety (11) were also commonly reported. Habit or autopilot behavior was recorded in 8 sessions, while CR emergencies and phone notifications were each reported 6 times. Headache was the least frequent trigger, appearing in 2 sessions.

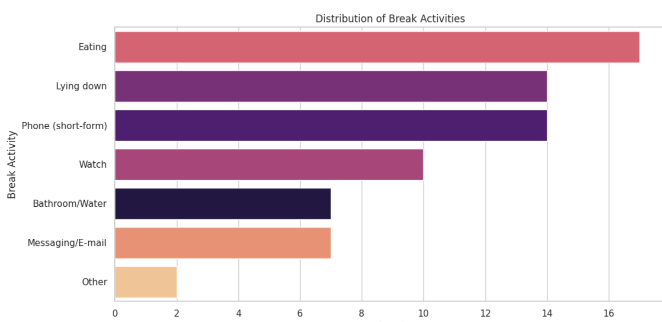

Fig. 8. Frequency of break activities recorded across 71 break sessions.

c) Distribution of Break Activities: Figure 9 shows the distribution of break activities in the dataset. The most frequently recorded activity was eating, with 17 occurrences, followed by lying down (14) and phone (short-form) (14). Watching content was recorded in 10 sessions, representing a moderate frequency. Less commonly reported activities included bathroom/water and messaging/e-mail, each occurring 7 times. The least frequent activity was other, recorded in 2 sessions.

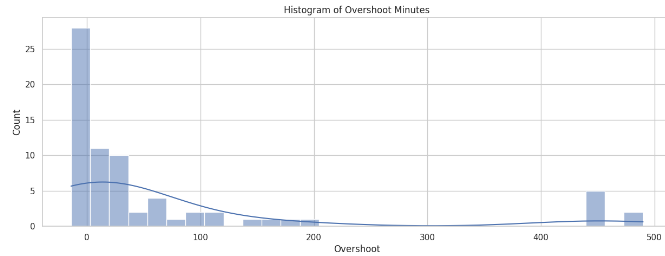

Fig. 9. Distribution of break overshoot durations (N = 71), showing the variability and extreme cases in break management.

d) Distribution of Overshoot Minutes: The distribution of overshoot minutes demonstrates a prominent positive (right) skew, with a significant concentration of data points located at the lower end of the scale. The primary peak occurs within the 0 to 25-minute interval, indicating that the majority of overshoot events are relatively brief. Following this initial cluster, the frequency of observations steadily declines, forming a sparse "long tail" that extends toward 500 minutes. The presence of several distinct, high-duration outliers between 420 and 490 minutes further emphasizes the non-normal nature of the dataset. An overlaid density curve illustrates the overall shape of the distribution, highlighting the contrast between the high-density region near zero and the isolated extreme values in the upper range.

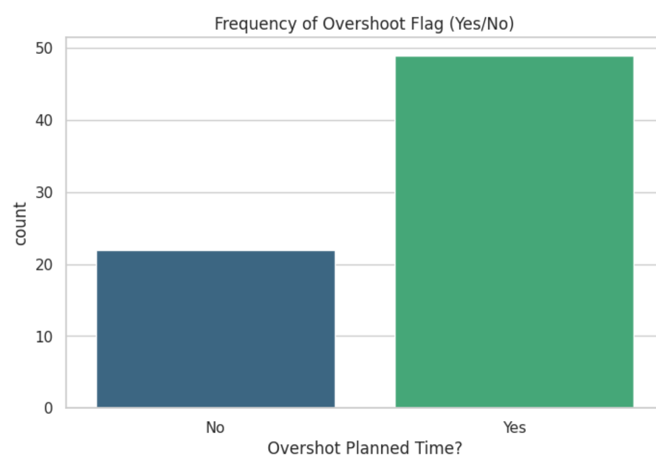

Fig. 10. Frequency of overshoot occurrences (N = 71), indicating whether breaks exceeded the planned duration.

e) Frequency of Overshoot Flag: Analysis of the overshoot flags reveals that the majority of breaks, approximately 69%, exceeded their planned duration. There is a clear imbalance between the categories, with 'Yes' (overshoot) occurring far more frequently than 'No' (returned on time). This pattern suggests that exceeding the scheduled break time is the dominant behavior in this dataset.

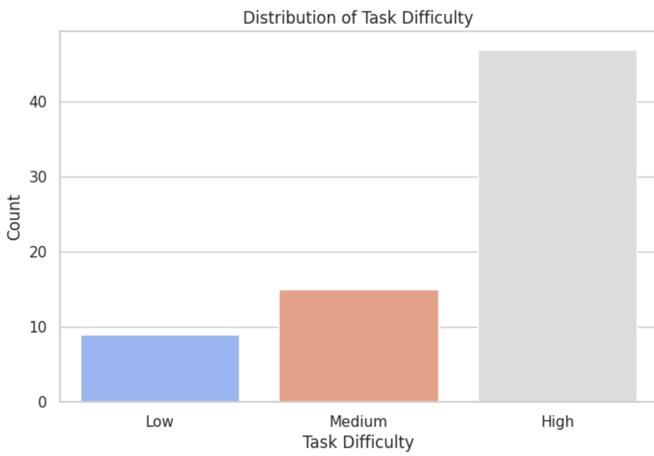

Fig. 11. Frequency distribution of perceived task difficulty levels across tracked sessions.

f) Distribution of Task Difficulty: The bar chart illustrates the categorical distribution of perceived task difficulty across the recorded sessions. The results show a strong concentration in the "High" difficulty category, which represents the majority of entries (count ¿ 45). In comparison, "Medium" and "Low" difficulty ratings were reported far less frequently, with approximately 15 and 9 occurrences, respectively. This distribution suggests that tasks were predominantly perceived as highly challenging during the data collection period.

Fig. 12. Distribution of post-break focus states (N = 71), showing how participant felt immediately after breaks.

g) Distribution of Post-Break Focus: Analysis of post-break focus states indicates that 'Neutral' is the most frequently reported feeling, followed closely by 'More focused'. Instances of 'More distracted' occur in several cases, suggesting that breaks do not always result in immediate improvements in attention or clarity. The least commonly reported state is 'More tired', implying that breaks generally help mitigate fatigue, even if they do not consistently enhance focus.

2) Factor-Wise Patterns:

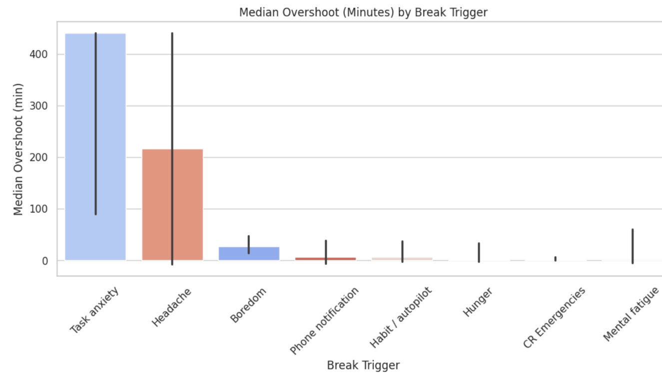

Fig. 13. Median overshoot duration by trigger category, showing the typical break extension associated with each condition.

a) Overshoot Duration by Break Trigger: Analysis of median overshoot durations indicates that Task anxiety and Headache are the most impactful triggers, producing median overshoots of approximately 440 minutes and 215 minutes, respectively. In contrast, triggers such as Phone notifications, Hunger, and Mental fatigue exhibit substantially lower median overshoot values, generally remaining below 10 minutes. These results suggest that anxiety-related or health-related triggers tend to be associated with substantially longer break extensions, while routine or physiological triggers correspond to shorter deviations from the planned duration.

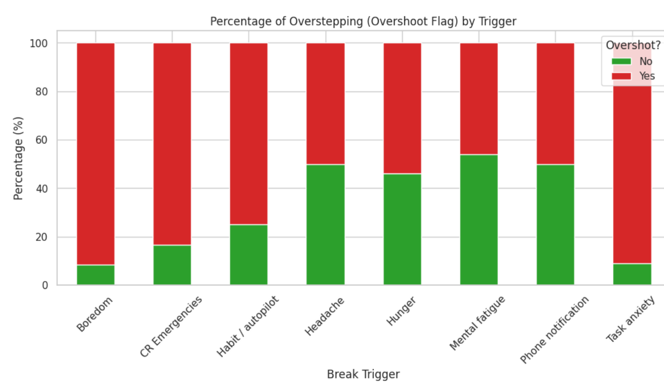

Fig. 14. Proportion of sessions exceeding planned duration for each trigger category

b) Percentage of Overshooting Flag by Break Trigger: When examining the likelihood of exceeding the planned break duration regardless of overshoot length, Boredom and Task anxiety emerge as the most persistent triggers, with over 90% of associated breaks resulting in an overshoot. Conversely, Mental fatigue shows the highest rate of on-time returns, with more than 50% of sessions finishing within the planned time window. This pattern indicates that certain triggers consistently lead to schedule deviations, whereas others are more compatible with maintaining planned break limits.

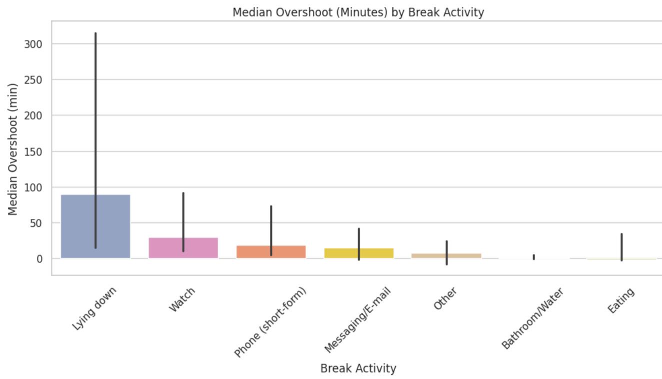

Fig. 15. Median overshoot duration grouped by break activity type.

c) Overshoot Duration by Break Activity: Analysis of median overshoot by activity shows that "Lying down" is associated with the highest typical overshoot, with a median of approximately 90 minutes, followed by "Watching" at roughly 30 minutes. In contrast, more functional or goal-oriented activities such as "Eating" and "Bathroom/Water" display negligible median overshoot values, generally remaining close to the planned duration. These findings suggest that passive, rest-oriented activities tend to correspond with longer break extensions, whereas short, task-focused activities are more time-bounded.

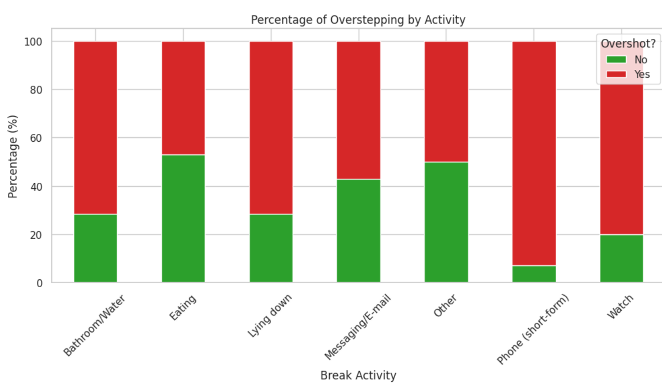

Fig. 16. Proportion of sessions exceeding planned duration for each activity category.

d) Percentage of Overshooting Flag by Break Activity: Categorical analysis further indicates that Phone use (short-form content consumption) is the most habitual contributor to break overstepping, with nearly 93% of such sessions exceeding the planned time. Conversely, breaks involving Eating or Other structured activities are comparatively easier to complete on schedule, with close to 50% of those instances finishing within the intended return window. This pattern highlights that media-consumption behaviors are strongly associated with schedule drift, whereas structured or necessity-based activities show higher adherence to planned timing.

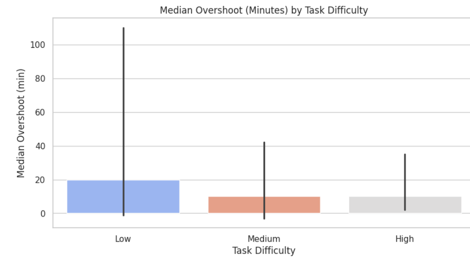

Fig. 17. Median overshoot duration across perceived task-difficulty levels.

e) Overshoot Duration by Task Difficulty: Comparison of median overshoot durations shows that the "Low" difficulty category recorded the highest typical overshoot, at approximately 20 minutes, whereas both "Medium" and "High" difficulty tasks show lower median values of roughly 10 minutes. This indicates that breaks taken during lower-difficulty tasks tend to extend slightly longer on average than those associated with more demanding work.

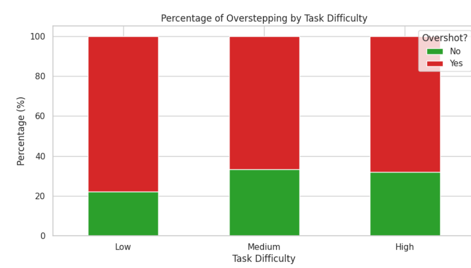

Fig. 18. Proportion of sessions exceeding planned duration for each difficulty level.

f) Percentage of Overshooting Flag by Task Difficulty: Despite the shorter median overshoot durations, high-difficulty tasks exhibit the highest rate of schedule overstepping, with nearly 70% of associated breaks exceeding the planned time. This pattern suggests that while demanding tasks may increase the likelihood of taking a break that runs over schedule, they may also encourage relatively quicker returns compared to breaks taken during lower-engagement tasks. These findings point to a distinction between the probability of overshooting and the length of the overshoot once it occurs.

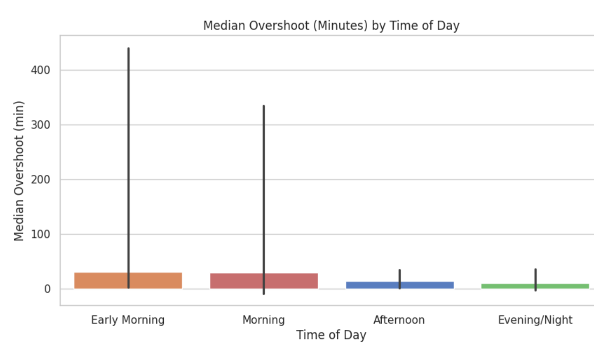

Fig. 19. Median overshoot duration across time-of-day periods.

g) Overshoot Duration by Time of Day: Temporal analysis shows that the highest median overshoot durations occur during the Early Morning and Morning periods, both averaging approximately 30 minutes. Median overshoot decreases substantially during the Afternoon and Evening/Night, falling to around 10 minutes or less. Although earlier periods exhibit considerable variability, as reflected by large error ranges, the central tendency indicates that breaks taken earlier in the day tend to extend longer than those taken later.

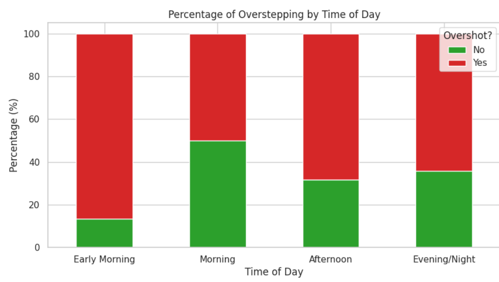

Fig. 20. Proportion of sessions exceeding planned duration by time-of-day.

h) Percentage of Overshooting Flag by Time of Day: The probability of exceeding the planned break duration varies notably across the day. The Early Morning period shows the highest volatility, with nearly 87% of breaks resulting in an overshoot. Timing reliability is greatest during the Morning, where approximately 50% of breaks conclude within the planned window, before adherence declines again in the Afternoon and Evening/Night periods. These findings suggest that both the duration and likelihood of overshooting are influenced by the timing of the break.

3) Factor Combinations:

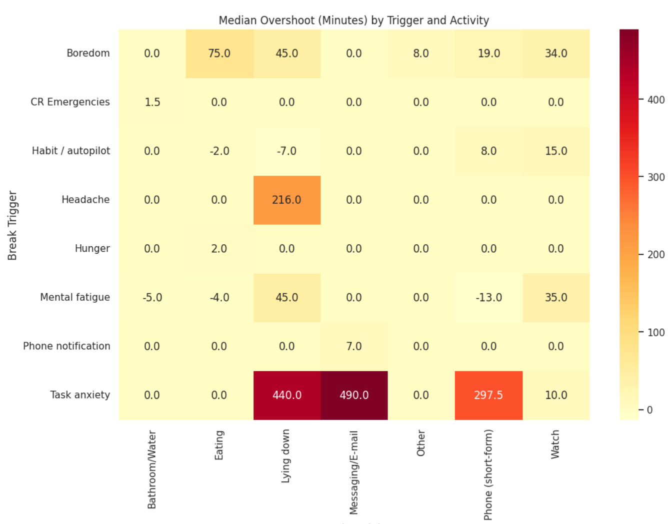

Fig. 21. Median Overshoot by Trigger and Activity.

a) Overshoot by Trigger–Activity Combination: The heatmap shows median overshoot duration (minutes) for each combination of break trigger and activity. The highest median overshoots occur for Task anxiety paired with Messaging/E-mail (490.0 minutes), Lying down (440.0 minutes), and Phone (short-form) (297.5 minutes). Other elevated median overshoots include Headache + Lying down (216.0 minutes) and Boredom + Eating (75.0 minutes). Most other combinations, including Bathroom/Water, CR Emergencies, or Other activities, show negligible or zero-minute median overshoots. Negative overshoot values are observed for Phone (short-form) + Mental fatigue (-13.0 minutes) and Lying down + Habit/autopilot (-7.0 minutes).

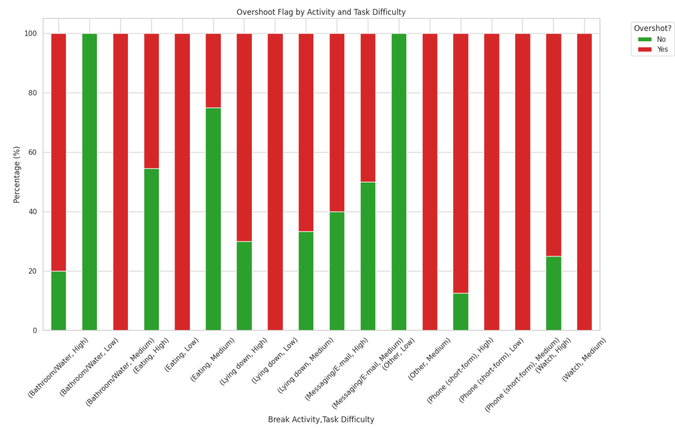

Fig. 22. Percentage of breaks exceeding planned duration by activity–difficulty combination.

b) Overshoot Flag by Activity and Task Difficulty: Some pairings had 100% overshoot (Lying down/Watching + High difficulty). Bathroom/Water + Low difficulty returned on time 100%.

B. Association / Correlation Analysis

TABLE III
SPEARMAN CORRELATION (RANK-BASED/MEDIAN-STYLE) BETWEEN TASK DIFFICULTY AND OVERSHOOT MINUTES

Correlation Coefficient	-0.0248
P-value	0.8374
Interpretation	No Significant Relationship

a) Correlation Between Task Difficulty and Overshoot Duration: A Spearman correlation was conducted to examine the relationship between task difficulty and overshoot minutes. The analysis revealed a negligible and non-significant correlation ($r_s = -0.025$, $p = 0.837$), indicating no detectable association between perceived task difficulty and the length of subsequent overshoots in this dataset.

C. Statistical Tests

Research Question 1: How do break triggers, break activities, task difficulty, and time of day relate to overshooting planned break durations

TABLE IV
KRUSKAL-WALLIS H-TEST RESULTS FOR THE EFFECT OF BREAK TRIGGER, ACTIVITY, TASK DIFFICULTY, AND TIME OF DAY ON OVERSHOOT DURATION.

Factor	H-Statistic	P-Value	Interpretation	Decision	Highest Impact Group
Break Trigger	17.6582	0.0136	Statistically significant	Reject H_{01}	Task anxiety
Break Activity	11.2168	0.0819	Not statistically significant	Fail to reject H_{02}	Lying down
Task Difficulty	0.3001	0.8607	Not statistically significant	Fail to reject H_{03}	Low
Time of Day	2.5717	0.4625	Not statistically significant	Fail to reject H_{04}	Early Morning

a) Significance of Factors Affecting Overshoot: The Kruskal-Wallis test indicated that Break Trigger had a statistically significant effect on overshoot duration (H = 17.66, p = 0.0136), with Task anxiety being the group with the highest overshoot. In contrast, Break Activity (H = 11.22, p = 0.0819), Task Difficulty (H = 0.30, p = 0.8607), and Time of Day (H = 2.57, p = 0.4625) did not have a statistically significant effect.

TABLE V
MANN-WHITNEY U TESTS FOR PAIRWISE COMPARISONS BETWEEN BREAK TRIGGERS.

Comparison	U-Statistic	P-Value	Significant
Task anxiety vs Hunger	127.0	0.0014	Yes
Task anxiety vs Mental fatigue	122.0	0.0036	Yes
Boredom vs Task anxiety	22.0	0.0072	Yes
CR Emergencies vs Task anxiety	6.0	0.0073	Yes
Task anxiety vs Habit / autopilot	76.0	0.0090	Yes
CR Emergencies vs Boredom	8.5	0.0114	Yes
Task anxiety vs Phone notification	58.0	0.0132	Yes

b) Post-Hoc Pairwise Comparisons of Break Triggers: To explore which specific break triggers contributed to the significant effect observed in the Kruskal-Wallis test, post-hoc pairwise Mann-Whitney U tests were conducted. The analysis revealed that breaks triggered by Task Anxiety resulted in significantly longer overshoot durations compared to Hunger (U = 127.0, p = 0.0014), Mental Fatigue (U = 122.0, p = 0.0036), Habit/Autopilot (U = 76.0, p = 0.0090), and Phone Notifications (U = 58.0, p = 0.0132). Task Anxiety also differed significantly from Boredom (U = 22.0, p = 0.0072) and CR Emergencies (U = 6.0, p = 0.0073). Additionally, CR Emergencies differed significantly from Boredom (U = 8.5, p = 0.0114). All reported p-values are below 0.05, supporting the rejection of the null hypothesis H_{01} and confirming that specific break triggers, particularly Task Anxiety, contribute to longer overshoot durations.

TABLE VI
EFFECT SIZE: ETA-SQUARED FOR BREAK TRIGGER ON OVERSHOOT RANKS

Eta-squared	0.1663
Interpretation	Large (0.14+)

c) Impact of Break Triggers on Overshoot Duration: The eta-squared value of 0.1663 indicates a large effect, confirming that the type of break trigger strongly influences how much breaks exceed their planned duration.

Research Question 2: Do breaks that overshoot their planned duration lead to better, worse, or unchanged post-break focus?)

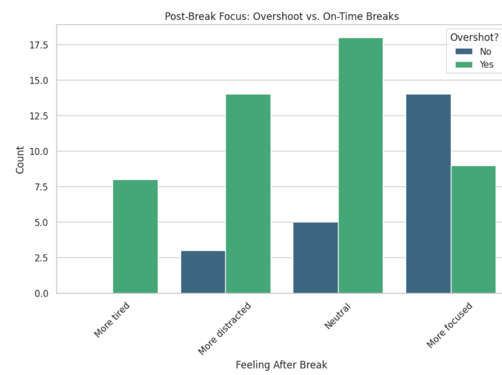

Fig. 23. Distribution of subjective focus levels following breaks by overshoot status.

d) Post-Break Focus: Overshoot vs. On-Time Breaks: The chart shows the number of sessions reporting each focus state after a break. For sessions that overshot the planned duration, participants most frequently reported feeling “Neutral” (18 sessions) or “More distracted” (14 sessions). In contrast, sessions that were on-time more often resulted in participants feeling “More focused” (14 sessions), compared with 9 sessions reporting this feeling after overshot breaks.

TABLE VII
COMPARISON OF POST-BREAK FOCUS BETWEEN ON-TIME AND OVERSHOOT BREAKS.

Overshoot Flag	Count	Median Focus	Mean Focus	Mean Rank	Median Label
No	22	2.0	1.50	48.91	Focused
Yes	49	1.0	0.57	30.20	Neutral

e) Impact of Overshooting on Post-Break Focus: Analysis of post-break focus shows that sessions that returned on time (n = 22) had a median focus rating of 2.0 and a mean rank of 48.91, corresponding to a “Focused” state. In contrast, sessions that overshot the planned duration (n = 49) had a median focus of 1.0 and a mean rank of 30.20, corresponding to a “Neutral” state.

TABLE VIII
MANN-WHITNEY U TEST FOR THE EFFECT OF OVERSHOOTING ON POST-BREAK FOCUS

Statistic	P-value	Result	Decision
255.0000	0.0002	Statistically Significant	Reject H_{05}

f) Effect of Overshooting on Post-Break Focus: A Mann-Whitney U test confirmed that breaks completed on time are associated with higher post-break focus compared to overshot breaks (U = 255.0, p = 0.0002), indicating a significant impact of overshooting on focus.

TABLE IX
POST-BREAK FOCUS: ON-TIME VS. OVERSHOT BREAKS

Measure	On-Time Breaks	Overshot Breaks
Median Focus	2.0 (Focused)	1.0 (Neutral)
U-statistic	255.0	
p-value	0.0002	
Rank-based Effect Size (r)	0.4191 (medium-to-large)	

g) Effect Size of Overshooting on Post-Break Focus: The rank-based effect size for the difference in post-break focus between On-Time and Overshot breaks was $r = 0.4191$, indicating a moderate-to-large effect. This suggests that On-Time breaks are meaningfully more likely to result in higher post-break focus compared to Overshot breaks.

D. Bias Consideration

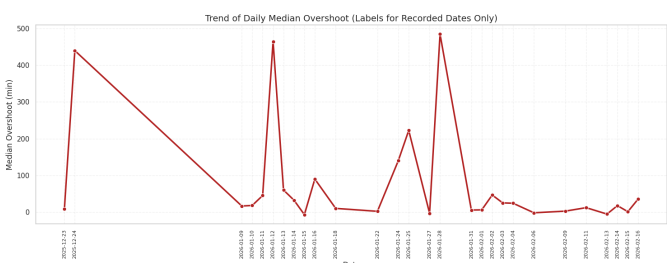

Fig. 24. Daily median overshoot duration (minutes) from late Dec 2025 to mid-Feb 2026.

a) Daily Median Overshoot Trends (Dec 2025–Feb 2026): Daily median overshoot exhibited substantial variability across the three-month period. Prominent peaks were observed on December 24, 2025 (440 minutes), January 12, 2026 (465 minutes), and January 28, 2026 (485 minutes), the latter representing the highest recorded value. Following January 28, median overshoot declined and remained comparatively low throughout February 2026, generally ranging between 0 and 50 minutes. A recording gap occurred between December 24, 2025, and January 9, 2026. Outside of peak days, median overshoot values were typically below 100 minutes.

TABLE X
MIXED-EFFECTS MODEL EXAMINING THE EFFECT OF BREAK TRIGGERS ON LOG-TRANSFORMED OVERSHOOT DURATION, WITH DATE INCLUDED AS A RANDOM GROUPING FACTOR.

Variable	Coef.	SE	z	p	[0.025]	[0.975]
Intercept	3.62	0.34	10.78	0.000	2.96	4.28
Q('Break_Trigger')[T.CR Emergencies]	-0.65	0.58	-1.13	0.26	-1.79	0.48
Q('Break_Trigger')[T.Habit / autopilot]	-0.32	0.52	-0.62	0.53	-1.34	0.69
Q('Break_Trigger')[T.Headache]	0.53	0.87	0.61	0.54	-1.18	2.23
Q('Break_Trigger')[T.Hunger]	-0.73	0.45	-1.61	0.11	-1.62	0.16
Q('Break_Trigger')[T.Mental fatigue]	-0.30	0.48	-0.63	0.53	-1.24	0.64
Q('Break_Trigger')[T.Phone notification]	-0.61	0.57	-1.07	0.28	-1.74	0.51
Q('Break_Trigger')[T.Task anxiety]	1.59	0.48	3.32	0.001	0.65	2.53
Group Var	0.14	0.17				

Significant Fixed Effects (p ¡ 0.05): Intercept, Q('Break_Trigger')[T.Task anxiety]

b) Mixed-Effects Model Results (Log-Transformed): The analysis showed that task anxiety was the only break trigger significantly associated with log-transformed overshoot duration ($\beta = 1.59$, SE = 0.48, $z = 3.32$, $p = 0.001$), indicating that anxiety-related breaks were linked to longer overshoot durations. All other triggers (CR emergencies, habit/autopilot, headache, hunger, mental fatigue, and phone notification) were not statistically significant ($p > 0.05$).

The model intercept was 3.62 (SE = 0.34, $p < 0.001$), representing the expected baseline value of log-transformed overshoot duration when no break trigger is present and predictors are at their reference levels. The variance of the random effect for date was 0.14, indicating that overshoot duration varied across different days, suggesting the presence of day-to-day fluctuations not explained by the break triggers alone.

V. DISCUSSION

A. Interpretation of Results

This study examined naturally occurring self-regulated breaks during academic work and investigated whether exceeding planned break durations influences post-break focus. The results indicate that break duration is influenced less by the activity performed during the break or the objective difficulty of the task, and more by the internal condition that initiated disengagement. Among the examined variables, task-related anxiety emerged as the most consistent factor associated with prolonged breaks and subsequent focus outcomes.

Descriptive analysis showed that a substantial proportion of breaks exceeded their planned duration, with approximately seventy percent classified as overshoots. However, the distribution of overshoot duration was strongly right-skewed. Most overshoots involved relatively small extensions, while a limited number of cases involved extremely long breaks. This pattern indicates that minor deviations from planned break length are common in natural study behavior, whereas very large disengagement episodes occur infrequently but substantially affect overall averages.

Inferential testing identified break trigger as the only variable that significantly predicted overshoot duration. Breaks initiated by task-related anxiety were significantly longer than those triggered by physiological needs, routine behaviors, or external notifications. One interpretation consistent with this pattern is that anxiety-triggered breaks may function as short-term emotional regulation responses. When a task generates stress, uncertainty, or perceived difficulty, disengaging from the task may temporarily reduce psychological discomfort. This temporary relief may delay task re-engagement, resulting in longer break durations compared with breaks taken for concrete physical needs, which typically conclude once the need is satisfied.

Analysis of break activities provided complementary descriptive information. Passive activities such as lying down, watching media, or short-form phone use were descriptively associated with longer overshoots; however, these differences were not statistically significant. This suggests that the specific activity undertaken during the break does not independently determine overshoot duration. Instead, activity choice may reflect the underlying disengagement context. Activities tied to functional completion (e.g., eating or restroom use) are inherently bounded, whereas passive activities lack clear completion markers, which may allow longer continuation when disengagement has already occurred.

Task difficulty showed only a weak relationship with overshoot behavior. Although higher-difficulty tasks slightly increased the likelihood that a break would exceed its planned duration, difficulty did not significantly predict the length of the overshoot itself. This indicates that objective workload alone is insufficient to explain prolonged disengagement. The findings therefore suggest that subjective response to the task, rather than technical difficulty per se, may play a more important role in determining break duration.

Time-of-day comparisons showed minor descriptive differences, with somewhat longer overshoots occurring earlier in the day, but these differences were not statistically significant. This suggests that while circadian or daily scheduling factors may influence when breaks occur, they do not reliably determine how long disengagement persists once a break begins.

With respect to post-break outcomes, a clear association was observed between break duration and subsequent focus. Breaks completed within their planned duration were associated with higher post-break focus ratings, whereas overshot breaks were more frequently followed by neutral or distracted states. The difference was statistically significant and exhibited a large effect size, indicating that extended breaks are linked to reduced readiness to resume focused work. This pattern is consistent with the interpretation that prolonged disengagement disrupts task continuity and increases the cognitive effort required to restart.

Finally, the mixed-effects model indicated that overshoot duration varied across dates, suggesting the presence of day-level influences not directly measured in the dataset. Such influences may include accumulated fatigue, sleep quality, workload variation, or contextual academic pressures. While these factors were not explicitly recorded, their inferred presence highlights the role of broader daily conditions in shaping real-world study behavior.

Overall, the findings support a consistent interpretation: internal triggers, particularly anxiety-related disengagement, are associated with longer break durations, and prolonged breaks are in turn associated with reduced post-break focus. Other examined factors, including activity type, task difficulty, and time of day, appear to contribute descriptively but do not independently predict overshoot duration when considered statistically. These results provide an empirically grounded account of how self-regulated breaks function in an authentic academic context.

B. Comparison to Related Work

The current findings align with prior research emphasizing the dual nature of breaks. Albulescu et al. [1] demonstrated that short breaks can improve well-being and task performance, particularly under sustained attention demands. The present study corroborates this insight, showing that returning from breaks on time supports higher post-break focus.

Consistent with Biwer et al. [2] and Smits et al. [3], self-regulated breaks were found to vary substantially in duration, often exceeding planned lengths. However, this study extends prior work by highlighting the specific role of emotional triggers, particularly anxiety, in driving extended disengagement. While structured break methods aim to optimize performance through fixed schedules, naturally occurring breaks demonstrate that internal states and affective responses may override planned intentions, particularly in high-anxiety contexts.

Additionally, the distinction between probability of overshoot and magnitude of overshoot adds nuance to the literature. While prior studies focused on average effects of break structure, the current findings reveal that even when breaks are likely to overshoot (e.g., during high-difficulty tasks), the extent of overshoot is influenced more by emotional triggers than task demands, suggesting a need to incorporate psychological states in models of break behavior.

C. Limitations

Several limitations should be considered:

- Sample context: This study focused on a single participant, allowing for detailed, within-person insights into break behavior, but patterns may vary in other individuals or contexts.
- Sample size: The dataset included 71 self-tracked study sessions. While sufficient for exploratory analysis, the small number of observations limits statistical power, may obscure some relationships, and allows extreme overshoot cases to disproportionately affect descriptive statistics.
- Self-reported measures: Break triggers, durations, and post-break focus were recorded by the participant, which may be influenced by perception or recall. Consistent recording practices were maintained to help mitigate this.

- Data coverage: Occasional gaps in recording may have influenced daily trend analyses.
- Observational design: While the study highlights clear associations between triggers and break overshoot, it does not establish causal relationships.
- Temporal dependencies: Consecutive breaks may influence each other, but sequential effects were not explicitly modeled.
- Skewed distributions: Extreme overshoot values required log transformation, reflecting the inherent variability of break behavior.

D. Recommendations and Future Work

Future studies may consider the following:

- Objective tracking: Complementing self-report with digital activity logs or wearable sensors could enrich understanding of break behavior in natural settings.
- Longer observation periods: Extending data collection may uncover broader temporal trends and variability in break patterns.
- Exploring triggers and strategies: Examining how specific interventions or coping strategies influence break duration, especially for anxiety-driven breaks.
- Contextual factors: Considering environmental, social, or task-related factors could provide a more holistic view of what shapes break behavior.

VI. Conclusion

This study examined how self-regulated study breaks occur in a natural academic setting and whether exceeding planned break durations affects the ability to regain focus afterward. By tracking break triggers, activities, duration, and post-break attention over time, the project aimed to better understand the behavioral and psychological patterns that shape everyday study productivity.

The key findings indicate that exceeding planned break time was common, with most recorded breaks lasting longer than originally intended. Among the factors examined, the trigger initiating the break showed the strongest influence on how long the break ultimately lasted. Breaks prompted by task-related anxiety tended to extend substantially longer than those taken for physical needs such as hunger, fatigue, or routine interruptions. In contrast, the specific activity performed during the break and the objective difficulty of the task did not independently determine break duration. The analysis also showed a clear outcome effect: breaks that ended within the intended time were more strongly associated with better post-break focus, while overshot breaks more often led to neutral or distracted return states.

From a personal perspective, the study revealed that prolonged breaks were not primarily caused by laziness, poor planning, or the type of activity chosen during the break. Instead, they were more closely tied to moments when academic tasks felt stressful, uncertain, or mentally overwhelming. This suggests that what initially appeared to be a time-management issue was often an emotional or cognitive response to the task itself. Recognizing this pattern helped clarify that improving productivity may depend less on strictly controlling break activities and more on identifying situations that trigger avoidance or hesitation before disengagement begins.

These insights can be applied in daily study practice by focusing on managing the start of disengagement rather than only the length of the break. For example, when a task begins to feel overwhelming, strategies such as breaking the task into smaller steps, clarifying instructions, or briefly planning the next action may help reduce anxiety before a break becomes necessary. Additionally, setting clearer return cues or structured short breaks may help preserve cognitive momentum and prevent extended disengagement. The findings suggest that awareness of internal triggers can be as important as external time-management tools in maintaining consistent focus.

In conclusion, this personal study demonstrates that study break behavior is shaped not only by schedule or workload but also by internal psychological responses to academic tasks. Within the observed dataset, task-related anxiety appeared to play a central role in extending break duration, which in turn affected the ability to regain focus. While the results are specific to this individual observation period, they provide meaningful insight into how emotional responses interact with self-regulated study habits. Understanding these patterns offers a practical foundation for improving daily productivity and supports the broader idea that effective study management involves both behavioral structure and awareness of one's cognitive and emotional states.

References

[1] P. Albulescu, et al., "Give me a break! A systematic review and meta-analysis on the efficacy of micro-breaks for increasing well-being and performance," *PLoS ONE*, vol. 17, no. 8, 2022. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0272460

[2] F. Biwer, W. Wiradhany, M. G. A. Oude Egbrink, and A. B. H. de Bruin, "Understanding effort regulation: Comparing 'Pomodoro' breaks and self-regulated breaks," *Br. J. Educ. Psychol.*, vol. 93, Suppl. 2, pp. 353–367, 2023. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/36859717/

[3] E. J. C. Smits, N. Wenzel, and A. de Bruin, "Investigating the effectiveness of self-regulated, Pomodoro, and Flowtime break-taking techniques among students," *Behav. Sci.*, vol. 15, no. 7, p. 861, 2025. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/40723645/

[4] NumIQo, "Kruskal-Wallis Test Tutorial," 2026. [Online]. Available: https://numiqo.com/tutorial/kruskal-wallis-test

[5] Laerd Statistics, "Mann-Whitney U Test Using SPSS Statistics," 2026. [Online]. Available: https://statistics.laerd.com/spss-tutorials/mann-whitney-u-test-using-spss-statistics.php

[6] Laerd Statistics, "Spearman's Rank-Order Correlation Statistical Guide," 2026. [Online]. Available: https://statistics.laerd.com/statistical-guides/spearmans-rank-order-correlation-statistical-guide.php

[7] A. Built-In, "Kruskal-Wallis test: What it is and how to use it," *Built-In*, 2026. [Online]. Available: https://builtin.com/articles/kruskal-wallis-test

[8] Lean Sigma Corporation, "Mann-Whitney testing with Minitab," *Lean Sigma Corporation*, 2026. [Online]. Available: https://leansigmacorporation.com/mann-whitney-testing-with-minitab/

[9] Simplilearn, "Spearman rank correlation," *Simplilearn*, 2026. [Online]. Available: https://www.simplilearn.com/tutorials/statistics-tutorial/spearmans-rank-correlation