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.

Keyword: 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?

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 [4]. 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 [5].

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 [6]. 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 chapter.

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 Excel spreadsheet. The following variables were recorded for every break:

- **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. The result is measured in minutes:

Overshoot = Actual Break (min) - Planned Break (min)

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, allowing analysis of how break characteristics and triggers relate to regained focus or attention.

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.

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.

Additionally, frequency counts were performed on categorical variables such as Break Trigger, Break Activity, and Task Difficulty to verify consistent labeling and identify any inconsistencies in category naming. This step ensured uniform category representation prior to analysis.

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.

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)

This encoding preserved the ordinal structure of the variables while enabling quantitative interpretation.

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.

1.1 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.

1.2 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.

1.3 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.

1.4 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.

1.5 Temporal Trends

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

2. Statistical Tests

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

2.1 Tests for Group Differences

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 (e.g., unusually long breaks such as 500 minutes) 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 [7], 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: *insert space for the image to be insert in latex)
[Built-In Kruskal-Wallis Reference]

Figure 1. *insert fig caption*

Where:

- **N** = total number of observations
- **k** = number of groups
- $\mathbf{R}_i$ = sum of ranks for group *i*

- **n**□ = 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.

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 [8]. 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: *insert space for the image to be insert in latex)
Lean Sigma Mann–Whitney Reference

Figure 2. *insert fig caption*

Where:

- $\mathbf{n_1}$, $\mathbf{n_2}$ = sample sizes of the two groups
- $\mathbf{R_1}$, $\mathbf{R_2}$ = sum of ranks for each group

The smaller of U_1 and U_2 is used as the test statistic.

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.

Effect Size – Eta-squared (η^2)
To complement significance testing, η^2 was computed to quantify the proportion of total variance in Overshoot Minutes explained by Break Triggers. This provides a sense of practical importance, not just statistical significance.

Formula: *insert space for the image to be insert in latex)

Figure 3. *insert fig caption*

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.

2.2 Tests for Association

Spearman Rank-Order Correlation
Spearman correlation was used to examine monotonic relationships between ordinal or numeric variables [9], 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: *insert space for the image to be insert in latex)
[Simplilearn Spearman Rank Correlation Reference]

Figure 4. *insert fig caption*

Where:

- **ρ** = Spearman's rank correlation coefficient
- **d_i** = difference between the ranks of each observation
- **n** = number of observations

Interpretation:

- ρ = +1 → perfect positive monotonic relationship
- ρ = −1 → perfect negative monotonic relationship
- ρ = 0 → no consistent monotonic relationship

2.3 Focus Outcome Testing (RQ2)

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 that exceeding planned breaks significantly affects post-break focus.

Effect Size – Cohen's d
Cohen's d was calculated to assess the magnitude of the difference in Post-Break Focus between On-Time and Overshoot breaks.

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Figure 5. *insert fig caption*

Where:

- X¯1\bar{X}_1X¯1 = mean of group 1
- X¯2\bar{X}_2X¯2 = mean of group 2
- SpS_pSp = pooled standard deviation, calculated as:

Formula: *insert space for the image to be insert in latex)

Figure 6. *insert fig caption*

- S12,S22S_1^2, S_2^2S12,S22 = variance of group 1 and group 2
- n1,n2n_1, n_2n1,n2 = sample sizes of the two groups

Interpretation:
0.2 = small, 0.5 = medium, 0.8 = large effect.

2.4 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: *insert space for the image to be insert in latex)

Figure 7. *insert fig caption*

Where:

- **Y_{i}□** = outcome variable (overshoot minutes)
- **β_0** = fixed intercept
- **β_1, β_2, …** = fixed-effect coefficients
- **X_{1i}□, X_{2i}□, …** = predictors
- **u□** ~ **N(0, σ_u²)** = random effect for Date
- **ε_{i}□** ~ **N(0, σ²)** = residual error

Interpretation of Coefficients:
Indicates predicted increase or decrease in overshoot minutes associated with each factor,

adjusted for day-level effects, providing a more accurate estimate of true relationships between predictors and overshoot duration.

IV. RESULTS

A. **Exploratory Data Analysis**

a. **Overall Dataset Characteristics**

Overall Descriptive Statistics (N=71)

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

Table 1. Mean, median, and standard deviation values for planned break duration, actual break duration, overshoot time, and encoded post-break focus.

Table 1 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 and a median of 39.00 minutes, with 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, demonstrating variability in the amount by which actual breaks exceeded planned durations.

The encoded post-break focus score had a mean of 0.86, a median of 1.00, and a standard deviation of 1.00, summarizing the distribution of reported focus outcomes following breaks.

Distribution of Break Triggers

Figure 8. *Frequency of break triggers recorded across 71 break sessions.*

Figure X 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.

Distribution of Break Activities

Figure 9. *Frequency of break activities recorded across 71 break sessions.*

Figure X 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.

Distribution of Overshoot Minutes

Figure 10. Distribution of break overshoot durations (N = 71), showing the variability and extreme cases in break management.

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.

Frequency of Overshoot Flag

Figure 11. Frequency of overshoot occurrences (N = 71), indicating whether breaks exceeded the planned duration.

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.

Distribution of Task Difficulty

Figure 12. Frequency distribution of perceived task difficulty levels across tracked sessions.

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.

Distribution of Post Break Focus

Figure 13. Distribution of post-break focus states (N = 71), showing how participants felt immediately after breaks.

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.

b. Factor-Wise Patterns

Overshoot Duration by Break Trigger

Figure 14. Median overshoot duration by trigger category, showing the typical break extension associated with each condition.

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.

Percentage of Overshooting Flag by Break Trigger

Figure 15. Proportion of sessions exceeding planned duration for each trigger category.

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.

Overshoot Duration by Break Activity

Figure 16. Median overshoot duration grouped by break activity type.

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.

Percentage of Overshooting Flag by Break Activity

Figure 17. Proportion of sessions exceeding planned duration for each activity category.

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.

Overshoot Duration by Task Difficulty

Figure 18. Median overshoot duration across perceived task-difficulty levels.

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.

Percentage of Overshooting Flag by Task Difficulty

Figure 19. Proportion of sessions exceeding planned duration for each difficulty level.

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.

Overshoot Duration by Time of Day

Figure 20. Median overshoot duration across time-of-day periods.

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.

Percentage of Overshooting Flag by Time of Day

Figure 21. Proportion of sessions exceeding planned duration by time-of-day period.

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.

c. Factor Combinations

Overshoot by Trigger–Activity Combination

Figure 22. Median Overshoot by Trigger and Activity.

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).

Overshoot Flag by Activity and Task Difficulty

Figure 23. Percentage of breaks exceeding planned durations for each combination of activity and task difficulty.

The chart displays the percentage of breaks that overstepped their planned duration across activity–difficulty combinations. Several pairings show a 100% overshoot rate, including Lying down and Watching during High difficulty tasks. Conversely, activities such as Bathroom/Water and Other during Low difficulty tasks show a 100% on-time return rate.

B. Association / Correlation Analysis

Correlation Between Task Difficulty and Overshoot Duration

Figure 24. Spearman rank-order correlation between perceived task difficulty and overshoot duration (minutes).

A Spearman correlation was conducted to examine the relationship between task difficulty and overshoot minutes. The analysis showed 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 within this dataset.

C. Statistical Test

Research Question 1:

Statistical Significance of Factors Affecting Overshoot

Table 2. Kruskal-Wallis H-test results for the effect of break trigger, activity, task difficulty, and time of day on overshoot duration.

The Kruskal-Wallis test indicated that Break Trigger had a statistically significant effect on overshoot (H = 17.66, p = 0.0136), with Task anxiety identified as the group with the highest impact. In contrast, Break Activity did not reach significance (H = 11.22, p = 0.0819), Task Difficulty showed no significant effect (H = 0.30, p = 0.8607), and Time of Day also had no significant impact (H = 2.57, p = 0.4625).

Post-Hoc Pairwise Comparisons of Break Triggers

Table 3. Mann-Whitney U tests for pairwise comparisons between break triggers, showing statistically significant differences in overshoot duration.

A series of post-hoc pairwise Mann-Whitney U tests were conducted to examine differences in overshoot duration between individual break triggers. The analysis revealed several significant comparisons. Breaks triggered by Task anxiety resulted in significantly longer overshoots than those associated with 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). Additionally, Task anxiety differed significantly from Boredom (U = 22.0, p = 0.0072) and CR Emergencies (U = 6.0, p = 0.0073), while CR Emergencies also showed a significant difference compared to Boredom (U = 8.5, p = 0.0114). All reported p-values were below 0.05, indicating that these trigger pairs exhibit statistically significant differences in overshoot duration.

Impact of Break Triggers on Overshoot Duration

Table 4. Measure of how much break triggers influence overshoot duration.

The impact of break triggers on overshoot duration was measured, with a calculated value of 0.1663. Using common guidelines for interpretation (0.01 = small, 0.06 = medium, 0.14 = large), this value represents a large effect. This indicates that the type of break trigger plays a strong role in determining how much breaks exceed their planned duration.

Research Question 2:

Post-Break Focus: Overshoot vs. On-Time Breaks

Figure 25. Distribution of subjective focus levels following breaks, separated by whether the break exceeded its planned duration.

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.

Impact of Overshooting on Post-Break Focus

Table 5. Comparison of post-break focus between on-time and overshot breaks.

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. A Mann-Whitney U test confirmed that this difference is statistically significant ($U = 255.0$, $p = 0.0002$), indicating that breaks completed on time are associated with higher post-break focus compared to overshot breaks.

Effect Size of Overshooting on Post-Break Focus

Figure X. Cohen’s d for the difference in post-break focus between on-time and overshot breaks.

The effect size for the difference in post-break focus between on-time and overshot breaks was calculated as Cohen’s $d = 1.02$. Using common benchmarks for interpretation (0.2 = small, 0.5 = medium, 0.8 = large), this value represents a large effect, indicating that returning on time is strongly associated with higher post-break focus compared to overshooting the planned duration.

Bias Consideration

Daily Median Overshoot Trends (December 2025–February 2026)

Figure 15. Daily median overshoot duration (minutes) from late December 2025 through mid-February 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.

Mixed-Effects Model Results (Log-Transformed)

Table 7. Mixed-effects model examining the effect of break triggers on log-transformed overshoot duration, with date included as a random grouping factor.

The analysis showed that Task anxiety was the only break trigger significantly associated with log-transformed overshoot duration ($\beta = 1.59$, $SE = 0.48$, $z = 3.32$, $p = 0.001$). 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 ($SE = 0.34$, $p < 0.001$). The variance of the random effect for date was 0.138, indicating day-level variability in overshoot duration.

V. Discussion

A. Interpretation of Results

The present study examined naturally occurring break behavior over 71 sessions, focusing on the factors associated with overshoot duration and their consequences on post-break focus. Overall, break overshoot was a systematic rather than random phenomenon, influenced by both internal triggers and contextual factors.

Task anxiety emerged as the strongest and most consistent predictor of overshoot duration. This effect persisted even after accounting for clustering of breaks within days using a linear mixed-effects model, suggesting that extended disengagement during anxiety-triggered breaks is a stable within-person pattern rather than merely a reflection of daily mood, workload, or fatigue. Breaks prompted by anxiety were substantially longer than those triggered by hunger, mental fatigue, habit/autopilot, phone notifications, or CR emergencies, indicating that emotional triggers play a more central role in prolonging breaks than physiological or routine factors.

Other break triggers exhibited meaningful descriptive differences but did not reach statistical significance in the mixed-effects analysis. For example, boredom and headache were associated with higher median overshoot values, whereas mental fatigue and physiological needs like hunger showed shorter overshoot durations and higher rates of on-time return. These patterns suggest that some triggers may interact with day-specific contextual factors, while others are less consistently related to extended disengagement.

Task difficulty did not significantly predict the length of overshoot, although high-difficulty tasks were descriptively associated with a higher probability of overshooting. This indicates a distinction between the likelihood of taking an extended break and the actual magnitude of overshoot once a break occurs, highlighting that cognitive load alone does not fully account for break extension; emotional and motivational factors appear more influential.

Break outcomes further demonstrated behavioral consequences. Breaks completed within the planned duration were associated with significantly higher post-break focus compared to overshot breaks (Cohen's $d = 1.02$), indicating that maintaining time boundaries supports effective cognitive re-engagement. Temporal analyses revealed that breaks taken earlier in the day, particularly during the Early Morning period, tended to overshoot more than those taken later, suggesting that daily rhythms may interact with self-regulation capacity.

Factor combinations also revealed that certain trigger–activity pairings add to overshoot. Task anxiety combined with passive activities like lying down or phone use produced the longest extensions, whereas structured or necessity-based activities (e.g., eating, bathroom) were typically completed on schedule. These findings highlight the interactive influence of psychological and behavioral factors in break management.

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.

1. **Sample context**: This study focused on a single participant, which allowed for detailed, within-person insights into break behavior but means that patterns may vary in other individuals or contexts.

2. **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.

3. **Data coverage**: There were occasional gaps in recording, which may have influenced daily trend analyses.

4. **Observational design**: While the study highlights clear associations between triggers and break overshoot, it does not establish causal relationships.

5. **Temporal dependencies**: Consecutive breaks may influence each other, but sequential effects were not explicitly modeled.

6. **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:

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

VI. Conclusion

This study explored naturally occurring, self-regulated break behavior over 71 study sessions, focusing on factors influencing break overshoot and its association with post-break focus. The findings provide meaningful insights into how personal tendencies and contextual factors shape real-world break patterns.

Key Findings

- **Break triggers matter:** Task anxiety emerged as the strongest predictor of extended breaks, consistently leading to longer overshoot durations even after accounting for day-level variability. Emotional triggers, such as anxiety, appeared to influence disengagement more strongly than physiological needs or routine cues, such as hunger or phone notifications.

- **Break activities influence duration:** Passive, rest-oriented activities like lying down or watching content were associated with longer breaks, while structured or necessity-driven activities, such as eating or bathroom breaks, were more likely to end on time.

- **Timing and task context:** Breaks taken earlier in the day tended to extend longer than those later in the afternoon or evening. High-difficulty tasks did not significantly lengthen overshoot duration but were associated with a higher probability of exceeding planned break times.

- **Impact on post-break focus:** Returning on time was strongly linked to higher post-break focus, whereas overshooting often corresponded to neutral or slightly distracted states. This suggests that maintaining planned break duration can support cognitive recovery and sustained attention.

Reflection

Through this self-tracking study, the participant gained a clearer understanding of personal habits and how internal states, such as anxiety, influence break behavior. By observing patterns where passive activities and emotional triggers led to extended breaks, the participant was able to reflect on the impact of disengagement on focus and productivity. This experience highlighted the value of intentional self-regulation and mindful decision-making during study sessions. It also offered practical insights for managing energy, balancing flexibility with structure, and maintaining attention, emphasizing that even small adjustments in break management can support more effective learning and work habits.

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