Evaluating the Association Between Early-Day Cognitive States and Habits on Late-Day Focus: A 26-Day Case Study

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***Abstract*—Traditional productivity models emphasize early-day momentum and distraction avoidance. This n-of-1 personal informatics study examined the within-day relationship between morning behaviors and evening focus over 26 days. Mann-Whitney U and Kendall's Tau (τ) analyses showed that early-day focus was not significantly associated with later performance ($\tau = -0.13, p = 0.41$), while early-day distraction positively correlated with evening focus ($\tau = 0.35, p = 0.03$). Non-work screen use had the largest impact on late-day focus ($d = 1.06, p = 0.021$). Caffeine and tiredness showed no significant effects. These findings suggest that early-day disengagement may serve as strategic recovery or "cognitive priming," supporting subsequent performance. Overall, productivity appears dynamic and state-dependent, highlighting the value of individualized, data-driven self-regulation.**

***Index Terms*—Personal Informatics, N-of-1 Study, Cognitive Priming, Effort-Recovery Model, Digital Distraction, Self-Regulation**

I. Introduction

Human productivity and attention fluctuate throughout the day. Intensive longitudinal and experience sampling studies show substantial within-person variation in motivation, engagement, and cognitive performance [1], indicating that daily focus is influenced more by situational and temporal factors than by stable traits like conscientiousness.

One explanation is the progress principle, which proposes that making progress in meaningful work increases motivation, positive affect, and subsequent performance [2]. Beginning the day with focused effort may therefore enhance later engagement, whereas early avoidance or distraction could reduce perceived progress and weaken subsequent focus.

Alternatively, effort–recovery models emphasize that continuous task engagement depletes cognitive and self-regulatory resources, while brief breaks restore attention and reduce fatigue [3]. Empirical evidence suggests that early-day "distractions," such as short non-work screen use, may function as recovery periods that support later performance [4].

Despite research on daily changes in procrastination, engagement, and recovery [1], [3], few studies have directly examined whether early-day cognitive and behavioral states are associated with later-day focus within the same individual. Advances in personal informatics and self-tracking now allow structured analysis of these relationships [5], offering granular insights into individualized self-regulation, especially in modern digital work where professional and leisure activities often overlap.

This study investigates whether early-day behaviors and cognitive states are associated with later-day focus, providing empirical evidence relevant to both behavioral momentum and recovery-based models of daily productivity.

Research Hypotheses

- H_0**:** There is no statistically significant association between early-day cognitive/behavioral factors and late-day focus levels.
- H_1**:** At least one early-day cognitive or behavioral factor is statistically significantly associated with late-day focus.

Specific Aims

The primary objective of this study is to identify how behaviors in the first few hours of the day relate to later-day focus. Specific aims include:

1) To quantify and categorize within-person fluctuations in subjective states (focus, distraction, tiredness) and behavioral habits (work started timing, screen use, caffeine, music) using an n-of-1 personal informatics framework.
2) To examine whether the association between early cognitive engagement and later focus aligns with the Progress Principle.
3) To investigate "Distraction" and "Non - Work Screen Use" as potential recovery mechanisms rather than mere task-avoidance behaviors.
4) To determine the comparative association of various early-day factors on later-day focus outcomes to identify the most reliable indicators of a productive afternoon.

Research Questions

- **RQ1:** To what extent do early-day subjective states, specifically focus and tiredness, associate with late-day focus outcomes, and do they support a linear momentum pattern?

- **RQ2:** How do cognitive states and behaviors classified as being ”distracted” (distraction level and non-work screen use) relate to later-day focus?
- **RQ3:** Do specific behavioral habits (caffeine, music) or temporal factors (timing) demonstrate a significant difference in mean late-day focus outcomes?
- **RQ4:** How can the observed temporal structure of focus be interpreted in relation to competing theoretical models of daily productivity?

II. Literature Review

A. Scope of Previous Behavioral and Productivity Research

Previous research in human productivity has primarily examined the relationship between personality traits, physiological states, and task execution patterns. Extensive literature exists on academic procrastination, sleep quality, and mood fluctuations as predictors of performance [6]. Specifically, studies have focused on how individuals manage their energy over multiple days when facing deadlines. Beyond macro-level procrastination, researchers have also explored the impact of micro-breaks - short, informal pauses from work and how these ”recovery” activities influence cognitive vigor and fatigue [8].

B. Data Collection and Analysis Methods in Existing Literature

Existing studies largely utilize two main methodologies: trait-based assessments and Experience Sampling Methods (ESM). In a prominent study by Di Nocera et al. (2023), the researchers used the Pure Procrastination Scale to categorize 55 university students into high and low procrastinators before tracking their productivity on multi-day writing tasks [7]. Analysis in such studies often involves group-level comparisons (e.g., ANOVA or t-tests) to find differences between ”types” of people. Conversely, micro-behavioral research often uses ESM, where participants are prompted at random intervals throughout the day to record their current focus and behavior via smartphone applications, allowing for a more granular look at within-day changes [9].

C. Main Findings of Prior Studies

The academic consensus on productivity is largely divided between two primary theoretical frameworks: the Progress Principle and the Effort-Recovery Model. In terms of macro-execution patterns, research by Di Nocera et al. found that ”High Procrastinators” often experience a significant increase in productivity as a deadline approaches, whereas ”Low Procrastinators” tend to maintain a steady, consistent pace with peak activity occurring during the intermediate stages of a task [7]. This suggests that for certain individuals, the psychological pressure of a looming deadline acts as a necessary focus trigger rather than a mere failure of willpower.

Complementing this is the study of micro-recovery benefits; meta-analyses of micro-breaks ranging from 30 seconds to 5 minutes indicate that these short mental resets can boost energy levels by as much as 40%. Such pauses are critical as they prevent ”desensitization” to repetitive or long-term tasks, allowing the cognitive system to re-engage with higher levels of attention after a brief period of distraction [3].

D. Limitations of Existing Research

Despite these theoretical advancements, current literature is constrained by several significant limitations, most notably the ”Trait vs. State” gap. The majority of existing studies, including the work by Di Nocera et al., categorize participants based on stable, longitudinal traits such as being a ”chronic procrastinator.” This approach often overlooks the n-of-1 perspective, which examines how an individual’s focus fluctuates from hour to hour based on immediate internal and external variables, regardless of their broad personality traits. Furthermore, there is a distinct lack of naturalistic research. Many productivity studies are confined to controlled laboratory settings or specific academic assignments, failing to examine how informal ”digital distractions,” such as non-work screen use, naturally integrate into a professional’s deep-work routine throughout a standard day.

E. Similarity and Differentiation from the Current Project

The present study shares thematic similarities with the work of Di Nocera et al. regarding the exploration of focus timing and the potentially counter-intuitive benefits of delaying deep cognitive effort. However, this research differentiates itself through its specific temporal granularity, variable scope, and individualized approach. While prior research often analyzes patterns across a span of 3 to 5 days, this project investigates fluctuations within daily time blocks, specifically comparing early-day habits to late-day focus outcomes.

Additionally, this study expands the variable scope by explicitly testing ”Non-work screen use” and ”Early Distraction” as dynamic recovery variables. Unlike previous literature that frequently treats distraction as a lack of task-oriented coping, this project explores these behaviors as potential recovery states. Finally, by utilizing a Personal Informatics approach, this study addresses the aforementioned ”n-of-1” limitation. It demonstrates that for the specific subject, early-day distraction may not signify task avoidance but may instead represent a localized version of ”strategic recovery” necessary to facilitate high-intensity focus in subsequent blocks.

III. Methodology

This section describes the experimental design, data acquisition process, and the analytical framework used to investigate the relationship between early-day behaviors and late-day cognitive outcomes.

A. Participant Profile

In accordance with the n-of-1 research methodology, the study was conducted with a single primary subject who also served as the lead researcher. The participant is a 23-year-old Filipino male and a senior Computer Science student at National University Manila. This self-study approach was selected to ensure high fidelity in data logging and to capture the nuanced, idiosyncratic nature of personal productivity patterns.

B. Data Collection and Instrumentation

Data were acquired over a 26-day longitudinal period from January 20, 2026, to February 15, 2026. A structured self-recording protocol was implemented using a digital spreadsheet interface (LibreOffice Calc). To facilitate within-day analysis, the data were collected in an "exploded" format; rather than a single entry per day, each workday was segmented into three unique block-level observations (Early, Mid, and Late). This structured logging approach over the 26-day collection period resulted in a raw dataset of 78 unique observation rows. This high-resolution, block-level structure is essential for the study's goal of identifying how early-day behaviors and states statistically relate to later-day focus outcomes.

C. Data Schema and Operational Definitions

The dataset comprises 12 distinct variables categorized into identifiers, ordinal self-ratings, and binary contextual indicators.

Feature Name	**Data Type**	**Description / Scale**
workday_id	String	Primary index and unique identifier for daily blocks (e.g., JAN20, FEB12, FEB15).
timestamp	Time	Recorded time marking the end of a specific block (e.g., 11:23:00 AM).
block	Categorical	Segment of the day, categorized as Early, Mid, or Late.
focus_level	Ordinal	Self-reported focus intensity on a scale of 1–5.
distraction_level	Ordinal	Self-reported scale (1–5) measuring procrastination and engagement in non-productive activities.
tired_level	Ordinal	Self-reported scale (1–5) representing subjective fatigue.
main_activity	String	Self-reported primary activity performed during the block (e.g., coding, studying, gaming).
work_started_since_wake	Binary	Indicator (0, 1) denoting whether work was performed in the block.
non_work_screen_use	Binary	Indicator (0, 1) recording whether non-work screen use occurred.
music_playing	Binary	Indicator (0, 1) recording whether music was played in the block.
caffeine_last_log	Binary	Indicator (0, 1) recording whether caffeine was consumed during the block.
primary_distractor	String	Self-reported primary distractor during the block (e.g., "gaming", "phone", "watching").

TABLE I: Variable Definitions and Measurement Scales

D. Data Preparation and Cleaning

A preprocessing pipeline was implemented to handle the raw data collected via manual entry to ensure structural integrity and suitability for statistical analysis.

1) Handling Missing Data and Type Conversion: Feature columns containing numeric data (both ordinal and binary) were first converted from string objects to numeric types. To address minor data loss in two observation blocks, basic imputation techniques were applied:

- Ordinal Features: `focus_level`, `distraction_level`, and `tired_level`. Missing values were imputed using the median of each feature's distribution.
- Binary Features: `work_started_since_wake`, `non_work_screen_use`, `music_playing`, and `caffeine_last_log`. Missing values were filled using the mode (i.e., the most frequent value) of each respective feature.
- Qualitative Features: `main_activity` and `primary_distractor`. Missing entries were retained as *NaN* to avoid introducing artificial or

speculative categorical data.

2) Categorical Mapping and Indexing: To reduce the dimensionality of the qualitative data, the `main_activity` strings were mapped into three master categories: Productive, Leisure, and Recovery. This allowed for a more direct comparison of activity types later down the line. Additionally, the `workday_id` index was converted into a formal datetime format, including the year, to ensure chronological sorting and accurate temporal indexing across the 26-day period.

3) Data Aggregation and Feature Engineering: A critical step in the preprocessing phase involved isolating the within-day relationships. To test the correlation of early-day states, the data were aggregated by `workday_id` to separate independent and dependent variables:

- Independent Variables: Features captured exclusively during the Early block (e.g., `early_focus`, `early_distraction`).
- Dependent Variable: The target variable, Late Focus, was engineered by calculating the mean `focus_level` of the subsequent Mid and Late blocks.

This aggregation ensures that the statistical models are testing ”early cursors” rather than simultaneous correlations, effectively maintaining the temporal order required to answer the research questions.

E. Statistical Analysis

The statistical analysis followed a multi-stage pipeline, beginning with exploratory data analysis (EDA) to validate assumptions, followed by non-parametric inferential testing.

1) Preliminary Data Exploration: A statistical summary was generated using the .describe() method to assess the central tendency and dispersion of the dataset before formal hypothesis testing. This was followed by a series of visualizations to understand the temporal nature of the data:

- Boxplots: Utilized to visualize the block-level distribution and medians of `focus_level`, identifying potential outliers and variance across different times of the day.
- Mean Line Plots (by Block): Implemented to observe the trend of average focus levels across the Early, Mid, and Late blocks.
- Longitudinal Line Plots: Generated to track both the raw and mean focus levels over the entire 26-day collection period, allowing for the identification of cyclical patterns or burnout trends.

2) Univariate Data Exploration: To determine the appropriate statistical models and assess data relationships, the distribution of individual features was examined through both visual and mathematical methods.

- Bivariate Distribution Analysis: A scatterplot was generated to examine the relationship between `early_focus_level` and `late_focus_level`. This visualization was used to inspect potential monotonic or non-linear patterns and to assess distribution density across ordinal levels.
- Feature Screening: A correlation matrix was computed to evaluate the strength and direction of associations between all ordinal early-day variables and the dependent variable (`late_focus`). For improved interpretability, the matrix was visualized as a color-coded heatmap to facilitate rapid identification of comparatively stronger relationships.
- Binary Feature Grouping: For binary variables, late-day focus was operationalized as the average of the Mid and Late blocks. These aggregated focus values were grouped according to the presence (1) or absence (0) of the corresponding early-day habit. Group differences were visualized using bar charts comparing mean `late_focus` across conditions.
- Comparative Mean Difference Analysis: A differential bar chart was constructed to illustrate the mean difference in `late_focus` between active and inactive groups across all binary features. Additionally, a horizontal bar chart was implemented to display Kendall's Tau correlation coefficients for all early-day variables, enabling direct comparison of association strength and direction.
- Categorical Frequency Analysis: A countplot was generated to examine the distribution of non-work screen use across the three primary `main_activity` categories (Productive, Leisure, Recovery), providing descriptive insight into behavioral clustering across activity types.

3) Inferential Statistical Methods: Given the ordinal and binary nature of the features and the relatively small sample size (N=26), non-parametric statistical methods were prioritized. This approach was selected to avoid the risk of overfitting inherent in linear regression models and to satisfy the assumption of non-normality in self-reported behavioral data.

- Kendall's Tau (τ): Measures correlation between ordinal early-day features (e.g., `tired_level`, `distraction_level`) and `late_focus`. Effective for small datasets with many tied ranks.

$$\tau = \frac{C - D}{\frac{1}{2}n(n-1)} \tag{1}$$

  where
  - C = number of concordant pairs,
  - D = number of discordant pairs,
  - n = total number of observations.

- Mann-Whitney U Test: Applied to binary features to test if distributions of `late_focus` differ between Active (1) and Inactive (0) groups.

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

  where
  - n_1 = number of observations in group 1 (Active),
  - n_2 = number of observations in group 2 (Inactive),
  - R_1 = sum of ranks for group 1.

- Kruskal-Wallis H-Test: Used for qualitative features with more than two levels (e.g., `main_activity`: Productive, Leisure, Recovery) to test if medians differ across groups.

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{3}$$

where
  - k = number of groups,
  - n_i = number of observations in group i,
  - R_i = sum of ranks for group i,
  - N = total number of observations across all groups.
- Cohen's d: Quantifies effect size for all statistically significant results (p ¡ 0.05) of binary features.

$$d = \frac{\bar{X}_1 - \bar{X}_2}{s_p} \tag{4}$$

where
  - $\bar{X}_1$, $\bar{X}_2$ = means of groups 1 and 2,
  - $s_p = \sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}}$ is the pooled standard deviation,
  - s_1^2, s_2^2 = variances of the two groups,
  - n_1, n_2 = sample sizes of the two groups.

4) Bias and Measurement Error Considerations: As this study utilizes self-reported data within an n-of-1 framework, it is important to acknowledge the role of subjective perception in the measurement of cognitive states. The ratings for focus, distraction, and tiredness are inherently tied to the participant's internal state and self-awareness at the time of logging. While these subjective ratings are a core component of personal informatics, specific measures were taken to mitigate common research biases:

- Hawthorne Effect: The awareness of being studied can often lead to improved performance. To mitigate this, data were logged after the completion of each block rather than during the work itself, allowing for a more naturalistic reflection of behavior.
- Measurement Error: Errors in manual entry were addressed during the preprocessing phase. By utilizing median and mode imputation, the study ensured that the few missing data points (2 blocks) did not skew the overall distribution of the longitudinal dataset.

IV. Results

This chapter presents the findings from the exploratory and inferential statistical analyses. Results are organized according to the primary research question examining whether early-day behavioral and cognitive variables are associated with late-day focus. Descriptive statistics are presented first, followed by correlation analyses and group comparisons.

block	count	mean	std	min	25%	50%	75%	max
early	26.0	2.461538	1.605759	1.0	1.0	2.0	4.00	5.0
late	26.0	2.846154	1.689788	1.0	1.0	3.0	4.75	5.0
mid	26.0	2.615385	1.471786	1.0	1.0	3.0	3.00	5.0

Fig. 1: Descriptive Statistics of Focus Level by Daily Block.

Summary statistics for the 26-day period show that mean focus increased sequentially throughout the day, peaking in the Late block (x=2.85). The Mid block was the most consistent (=1.47), whereas the Late block showed the highest dispersion (=1.69). All segments utilized the full 1–5 scale, with the median focus rising from 2.0 in the morning to 3.0 in the afternoon and evening.

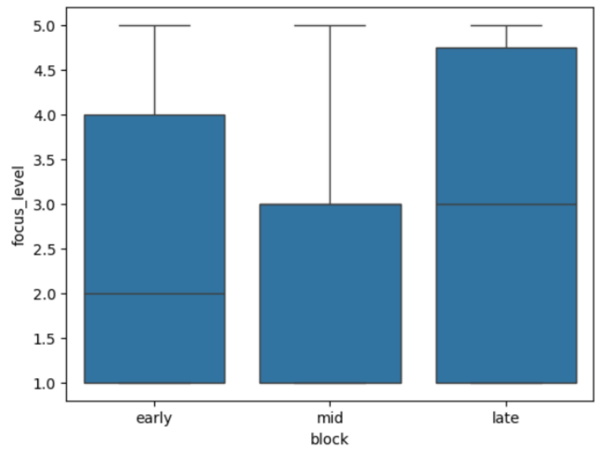

Fig. 2: Distribution of Focus Level by Daily Time Block

This boxplot illustrates the dispersion of focus levels across the three daily segments. Median focus levels increase from 2.0 in the Early block to 3.0 in both the Mid and Late blocks. While all segments utilized the full scale (1.0 – 5.0), the Late block shows the highest 75th percentile, whereas the Mid block displays the most condensed Interquartile Range (IQR), reflecting the consistency identified in the summary statistics.

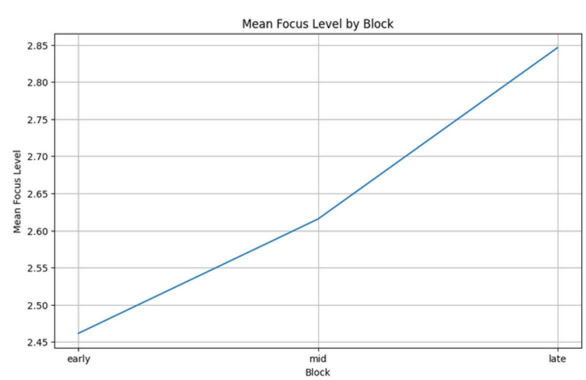

Fig. 3: Mean Focus Level Progression by Daily Time Block

This line graph illustrates the trend of average focus performance throughout the day. The data shows a steady upward progression, beginning at a mean of approximately 2.46 in the early block, rising to 2.62 in the mid block, and reaching a daily peak of 2.85 in the late block.

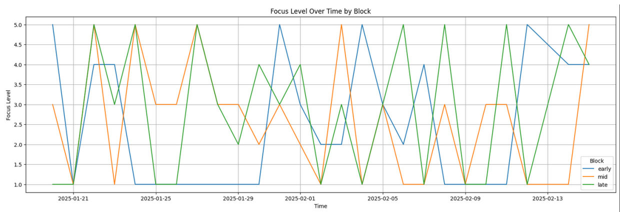

Fig. 4: Longitudinal Focus Level Trends by Block

This time-series plot tracks the daily focus levels for the early, mid, and late blocks over the 26-day study period from late January to mid-February. The data shows high day-to-day volatility across all three segments, with focus scores frequently fluctuating between the minimum (1.0) and maximum (5.0) values. No long-term upward or downward trend is immediately visible across the total duration of the study, though short-term cyclical patterns are present.

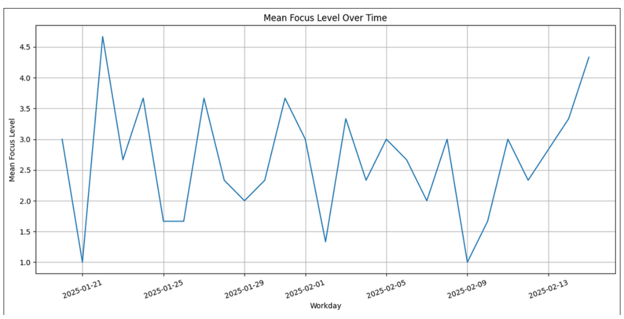

Fig. 5: Daily Mean Focus Level Over Time

This time-series chart displays the daily average focus level across the 26-day study period, calculated by averaging the early, mid, and late blocks for each workday. The data shows significant day-to-day volatility, with mean focus levels ranging from a minimum of 1.0 to a peak of approximately 4.7. While the progression is characterized by frequent fluctuations, a notable upward trend in average daily focus is observed during the final week of the study period.

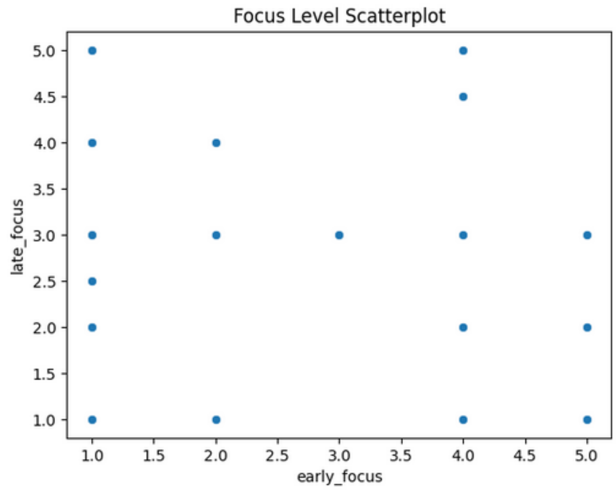

Fig. 6: Bivariate Relationship Between Early and Late Focus

This scatterplot displays the relationship between focus levels recorded in the early block and the corresponding focus levels in the late block. The data points are dispersed across the ordinal grid with no apparent linear clustering. The high density of points at the coordinates (1.0, 1.0) and (1.0, 3.0) reflects the frequency of low early-day focus scores relative to varied afternoon outcomes.

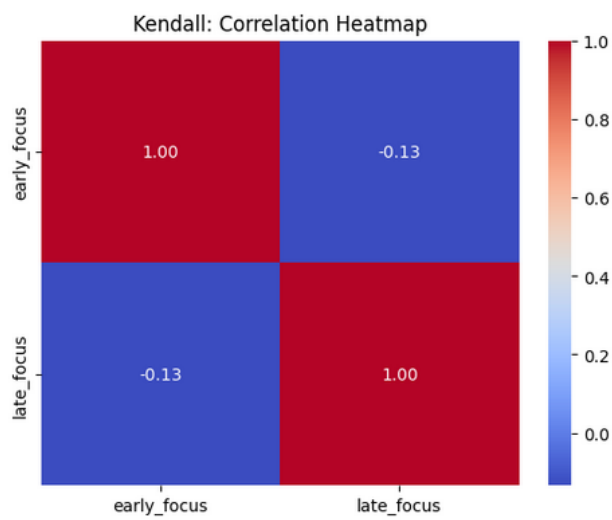

Fig. 7: Kendall Correlation Heatmap of Focus Segments

This heatmap visualizes the Kendall correlation coefficient between focus levels in different time blocks. The analysis reveals a weak negative correlation of -0.13 between early-day focus and late-day focus, indicating a negligible inverse relationship between the two variables within this dataset.

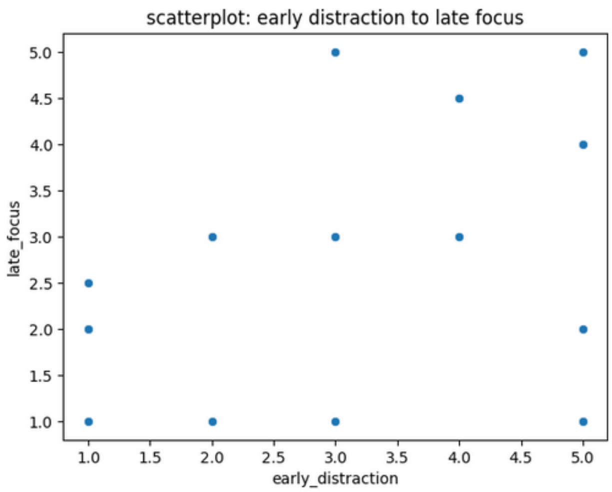

Fig. 8: Bivariate Relationship Between Early Distraction and Late Focus

This scatterplot visualizes the relationship between the level of distraction recorded in the early block and the focus level achieved in the late block. The data points are dispersed across the ordinal scale; however, the density of points indicates that high late-day focus (scores of 4.0 or 5.0) occurred across various levels of early-day distraction, while low early-day distraction (1.0) was associated with late-day focus scores ranging from 1.0 to 2.5.

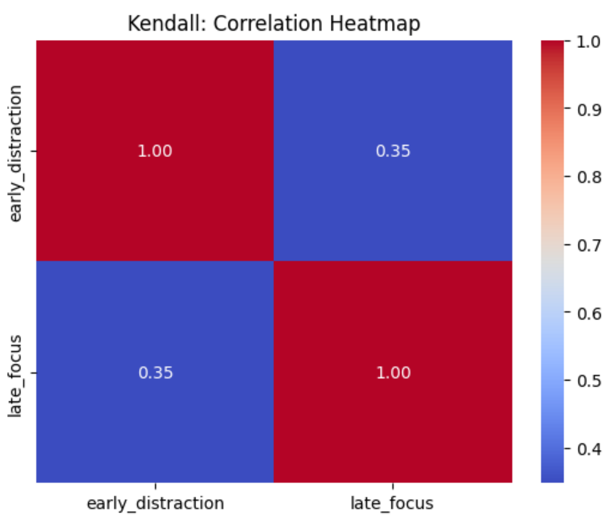

Fig. 9: Kendall Correlation Heatmap: Early Distraction vs. Late Focus

This heatmap displays the Kendall correlation coefficient between early-day distraction and late-day focus. The analysis reveals a positive correlation of 0.35, identifying early-day distraction as being moderately associated with late-day focus outcomes in this study.

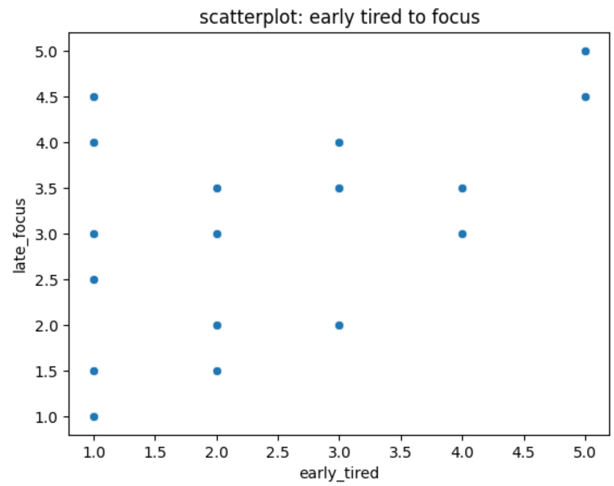

Fig. 10: Scatterplot of Early Tiredness to Late Focus

This scatterplot displays the relationship between tiredness levels recorded in the early block and corresponding focus outcomes in the late block. The distribution shows that the highest focus scores in the late block (4.5 and 5.0) were recorded on days where early-day tiredness was at its maximum recorded value of 5.0.

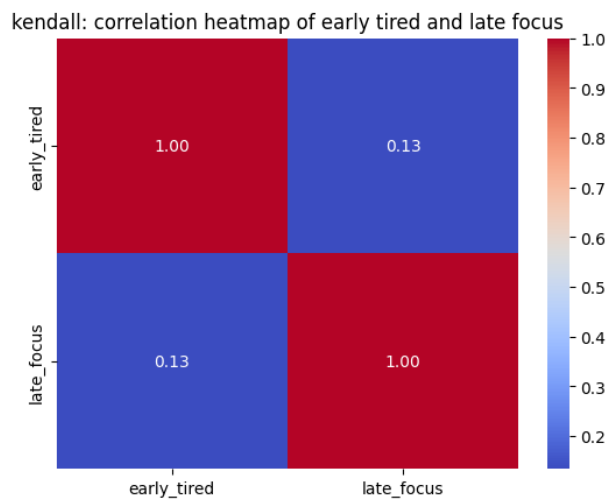

Fig. 11: Correlation Heatmap: Early Tiredness vs. Late Focus

This heatmap displays the correlation coefficient between tiredness levels recorded in the early block and subsequent focus levels in the late block. The analysis yields a coefficient of 0.13, indicating a very weak positive relationship between morning tiredness and afternoon focus outcomes within this dataset.

Comparison	τ	p	Sig.	H_0
Early vs. Late Focus	-0.13	0.41	No	Accepted
Early Distraction vs. Late Focus	0.35	0.03	Yes	Rejected
Early Tired vs. Late Focus	0.13	0.40	No	Accepted

TABLE II: Kendall Correlation of Ordinal Features with Late-Day Focus, showing significance and H_0 decisions.

This table presents the Kendall correlation results for ordinal early-day features and their relationship with late-day focus. Early-day distraction showed a moderate positive correlation with late-day focus, which was statistically significant, leading to rejection of the null hypothesis. In contrast, early-day focus and early-day tiredness exhibited weak correlations that were not statistically significant, and the null hypothesis for these features was accepted.

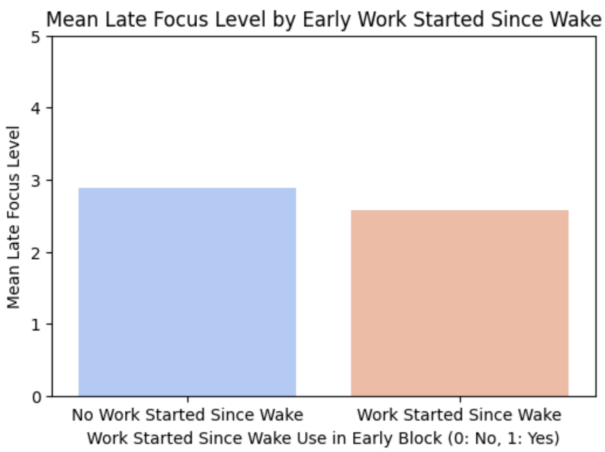

Fig. 12: Impact of Early Work Commencement on Late-Day Focus

This bar chart compares the mean late-day focus levels based on whether work was started in the early block. Days where work was not started immediately yielded a higher mean late-day focus of 2.88, compared to 2.58 on days where work began shortly after waking.

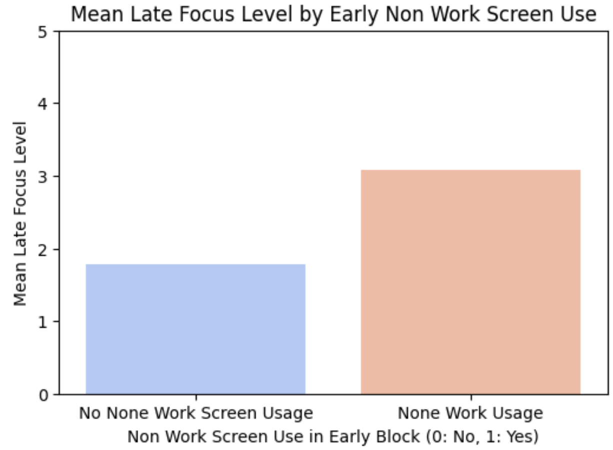

Fig. 13: Impact of Early Non-Work Screen Use on Late-Day Focus

This bar chart illustrates the difference in mean late-day focus based on the presence of non-work screen usage during the early block. Days involving early non-work screen use resulted in a higher mean late-day focus of 3.08, compared to 1.79 on days without such usage.

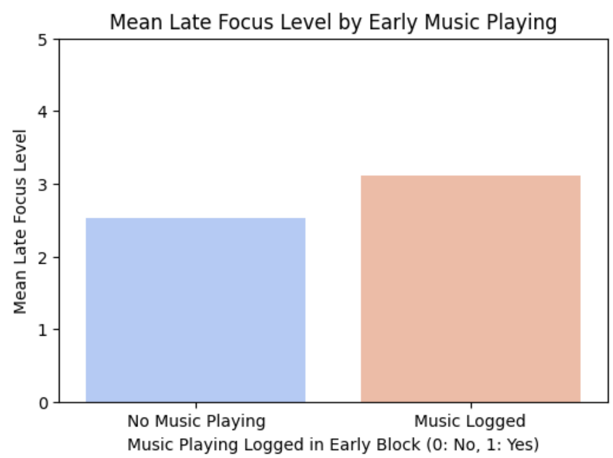

Fig. 14: Impact of Early Music Playing on Late-Day Focus

This bar chart compares the mean late-day focus levels based on whether music was playing during the early block. Days where music was playing in the morning resulted in a higher mean late-day focus of 3.11, compared to 2.53 on days without music.

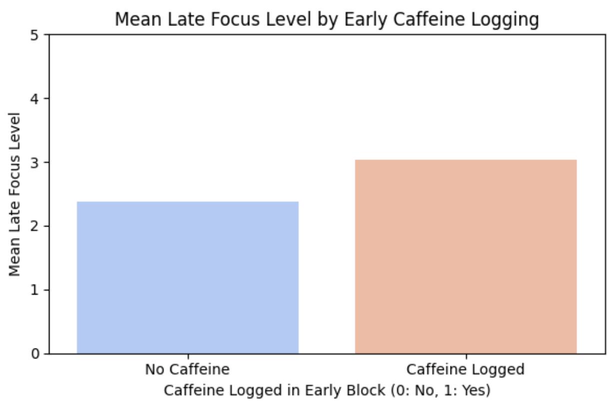

Fig. 15: Impact of Early Caffeine Logging on Late-Day Focus

Days where caffeine was consumed in the morning resulted in a mean late-day focus of 3.04, compared to 2.38 on days without caffeine.

	feature	p_value	mean_diff	cohens_d
0	work_started_since_wake	0.600569	-0.307692	-0.227246
1	caffiene_last_log	0.247966	0.660714	0.500679
2	non_work_screen_use	0.021347	1.293233	1.055039
3	music_playing	0.308671	0.581699	0.436492

Fig. 16: Mann-Whitney U Test Results and Effect Sizes for Binary Early-Day Habits

This table summarizes the Mann-Whitney U test results for binary early-day habits and their association with late-day focus. Non-work screen use was the only habit showing a statistically significant effect (p = 0.021) with a large effect size (d = 1.06), leading to rejection of the null hypothesis. Caffeine consumption (d = 0.50) and music playing (d = 0.44) had moderate effect sizes but were not statistically significant, and the null hypothesis was accepted for these variables. The timing of work commencement showed minimal impact on late-day focus ($d = -0.23$, p = 0.601), with the null hypothesis also accepted.

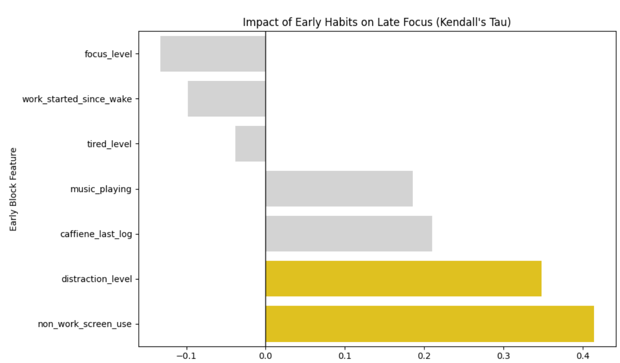

Fig. 17: Comparative Impact of Early-Day Variables on Late-Day Focus

This horizontal bar chart ranks both ordinal and binary early-day variables based on their Kendall's Tau (τ) correlation with late-day focus levels. Non-work screen use ($\tau = 0.41$) and distraction level ($\tau = 0.35$) are the only factors highlighted in yellow, indicating a statistically significant positive relationship with evening performance. Other factors, such as caffeine consumption ($\tau = 0.21$) and music playing ($\tau = 0.19$), show weaker positive associations. Conversely, tiredness ($\tau = -0.04$), the timing of work commencement ($\tau = -0.10$), and early focus levels ($\tau = -0.13$) exhibit negative correlations with late-day focus outcomes.

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Kruskal-Wallis H-test statistic: 1.09
P-value: 0.579
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Fig. 18: Late-Day Focus by Early Activity Category

This analysis assessed whether late-day focus differed across early-day activity categories using a Kruskal-Wallis H-test. The test yielded H = 1.09, p = 0.579, indicating no statistically significant difference, and the null hypothesis was accepted.

activity_category	No Screen Use (0)	Screen Use (1)	Total Entries	% Screen Use
Leisure	1	15	16	93.75
Productive	12	28	40	70.00
Recovery	11	8	19	42.11

Fig. 19: Distribution of Non-Work Screen Use by Activity Category

This table provides a percentage breakdown of non-work screen usage within each activity type recorded during the early block. The data shows a strong association between "Leisure" and morning screen use (93.75%), while "Recovery" activities were the least likely to involve early-block screens (42.11%).

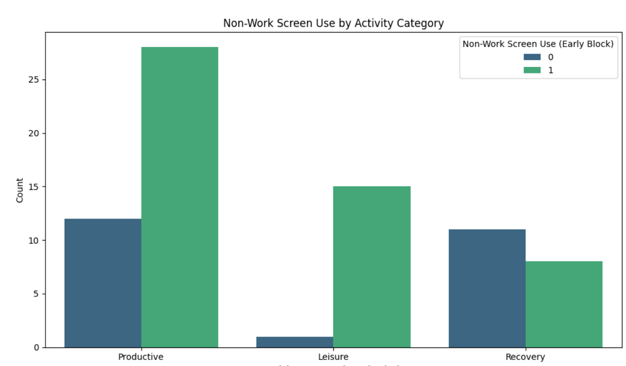

Fig. 20: Summary of Screen Use Frequency by Morning Activity

This grouped bar chart displays the frequency of early-block non-work screen usage across three primary activity categories: Productive, Leisure, and Recovery. The data indicates that "Productive" activities had the highest volume of screen use occurrences, while the "Leisure" category showed the highest proportional rate of screen engagement. Conversely, the ”Recovery” category exhibited the highest frequency of sessions completed without non-work screen use.

V. Discussion

This study examined whether early-day behavioral and cognitive variables were associated with late-day focus outcomes within a 26-day, n-of-1 personal informatics framework. Unlike traditional productivity research that emphasizes stable personality traits or multi-day execution patterns, this project investigated within-day fluctuations and tested whether behaviors commonly categorized as “distractions” might instead function as recovery mechanisms. The findings provide insight into how short-term behavioral states interact with later performance and contribute to the broader Trait vs. State discussion in productivity research.

1) Early Focus and the Limits of the Momentum Assumption: The results indicated no statistically significant relationship between early-day focus and late-day focus ($\tau = -0.13$, $p = 0.41$). This challenges the intuitive “momentum” assumption that a productive morning necessarily leads to a productive afternoon. Within the context of this study, late-day focus did not appear to be a continuation of earlier cognitive state.

This finding supports the idea that daily productivity may be segmented rather than cumulative. Instead of operating under a linear carryover model, focus levels may reset between blocks depending on context, task type, or behavioral adjustments. From a State-based perspective, performance appears more responsive to immediate contextual factors than to residual cognitive carryover from earlier blocks.

2) Early Distraction as a Potential Recovery Mechanism: The most theoretically significant finding was the moderate positive association between early-day distraction and late-day focus ($\tau = 0.35$, $p = 0.03$), a result that directly engages with the Effort–Recovery Model discussed in Chapter 2. While conventional productivity discourse often treats distraction as inherently detrimental, micro-break literature suggests that brief disengagement periods can restore attentional resources and reduce cognitive desensitization. Within the context of this dataset, early distraction may therefore have functioned less as avoidance and more as a transitional recovery phase that supported stronger engagement later in the day. This interpretation aligns with research indicating that short intervals of cognitive disengagement can increase subsequent vigor and task persistence. Accordingly, for this individual, distraction did not uniformly signal task failure but may have operated as a strategic reset that prevented premature depletion of attentional resources. However, this finding should be interpreted cautiously, as the observed effect likely reflects moderate, time-limited disengagement rather than prolonged or uncontrolled avoidance behavior.

3) Early Tiredness and Adaptive Compensation: Early-day tiredness did not show a significant association with late-day focus ($\tau = 0.13$, $p = 0.40$). This may reflect adaptive behavioral compensation. Individuals may offset subjective fatigue through environmental adjustments, caffeine, task selection, or motivational recalibration. Within a State-based framework, tiredness alone may not determine performance unless combined with other constraints.

4) Binary Early-Day Habits: Among the binary features, non-work screen use demonstrated the strongest effect ($d = 1.06$, $p = 0.021$), indicating a substantial practical difference in late-day focus outcomes. Notably, days involving early non-work screen engagement were associated with higher mean late-day focus, a pattern that directly challenges prevailing assumptions that digital exposure necessarily impairs subsequent cognitive performance. Rather than functioning purely as distraction, limited early screen use may have operated as a controlled disengagement phase, potentially aligning with recovery-based interpretations discussed earlier.

Caffeine consumption ($d = 0.50$) and music playing ($d = 0.44$) yielded moderate effect sizes but did not reach statistical significance, suggesting possible but inconsistent influence. Within the Effort–Recovery framework, caffeine may serve as an external stimulant compensating for emerging fatigue, while music may modulate arousal or enhance environmental engagement. However, the absence of statistical significance indicates that these effects were either variable across days or contingent on contextual moderators not captured in the present dataset.

In contrast, the timing of work commencement relative to waking demonstrated minimal impact ($d = -0.23$), suggesting that immediate task initiation does not necessarily translate into improved later performance. Collectively, these findings reinforce the broader conclusion that early-day behaviors may influence later focus in more complex and individualized ways than conventional productivity narratives assume.

5) Early Activity Category and Contextual Framing: The categorical type of early-day activity did not demonstrate a statistically significant association with late-day focus (H = 1.09, p = 0.579). This suggests that the broad classification of early activity (Productive, Leisure, Recovery) may be less strongly associated with later performance than the underlying behavioral components embedded within those categories.

While activity type itself was not a significant differentiator, descriptive analysis indicated variation in non-work screen usage across categories. Notably, Leisure sessions were most frequently associated with early screen exposure, whereas Recovery sessions were least likely to involve screens. This pattern suggests that behavioral mechanisms (e.g., screen engagement) may operate independently of categorical activity labels.

From a theoretical standpoint, this finding implies that the functional role of early-day behavior may depend more on the specific regulatory processes involved (stimulation, disengagement, arousal modulation) than on the nominal activity classification. In other words, the cognitive consequence of an activity may not be determined solely by whether it is labeled “productive” or “leisure,” but by how it influences attentional state.

6) Temporal Structure of Daily Focus: The observed upward progression across daily blocks contrasts with classical ego depletion theory, which suggests a gradual cognitive decline following sustained effort. Rather than showing progressive deterioration, the results suggest adaptive recalibration across the day, potentially reflecting delayed peak performance or strategic energy allocation. In addition, although substantial day-to-day variability was present, no strong longitudinal decline emerged across the 26-day observation window. This pattern indicates that short-term fluctuations in focus were more dominant than cumulative macro-level fatigue effects, reinforcing the view that daily cognitive performance may be governed more by dynamic regulation processes than by linear depletion models.

A. Comparison to Prior Research

The findings partially align with both the Progress Principle and the Effort–Recovery Model while simultaneously challenging certain assumptions embedded within each framework. The absence of a significant momentum effect contrasts with simplified interpretations of productivity accumulation, which assume that early effort reliably carries forward into later performance. Instead, the results support research suggesting that cognitive performance fluctuates according to contextual triggers and short-term regulatory processes rather than following a stable daily trajectory. Moreover, the positive association between early distraction and later focus offers tentative support for micro-break literature emphasizing cognitive replenishment. While traditional perspectives frame distraction as inherently counterproductive, the present findings suggest that limited early disengagement may facilitate later performance, potentially functioning as a preparatory or recovery mechanism. This pattern also echoes elements of procrastination research, such as the work of Di Nocera et al., which demonstrated that certain individuals experience performance surges following delayed initiation. In a similar manner, early disengagement in this study may have operated as a psychological precursor to intensified later effort. Collectively, these findings help narrow the Trait vs. State gap identified in prior productivity research. Rather than classifying the subject within a fixed productivity type, the findings demonstrate that performance states fluctuate dynamically within the same individual, reinforcing the importance of within-person analysis in understanding real-world productivity patterns.

B. Limitations

First, the study involved a single participant ($n = 1$), limiting generalizability. The findings represent an individual case study rather than population-level evidence. Second, all key variables were self-reported using a 1–5 ordinal scale. Subjective measurement introduces potential bias, including mood-dependent reporting and retrospective distortion. Third, the 26-day data collection window restricts longitudinal inference. Longer time horizons may reveal trends not detectable within a short interval. Fourth, the absence of controlled variables such as sleep duration, task complexity, academic workload, or stress levels limits causal interpretation. These unmeasured factors may confound observed associations. Finally, the relatively small number of observations reduces statistical power, increasing the risk of Type II error.

C. Recommendations and Future Work

Future research should expand upon this exploratory design by incorporating multiple participants to increase generalizability and statistical robustness. Extending the data collection period to several months would allow for the examination of seasonal, academic, or workload-related trends. Incorporating objective measures such as digital screen-time logs, wearable sleep tracking, or automated productivity metrics would reduce reliance on self-report data. Additionally, modeling approaches such as mixed-effects regression or time-series analysis could capture lagged and interaction effects between early-day and late-day variables.

Future studies may also examine additional variables, including sleep duration, stress levels, task type, and environmental context. Exploring nonlinear relationships and threshold effects may further clarify whether moderate distraction differs from excessive distraction in its impact on performance.

D. Conclusion

This study examined whether early-day behavioral and cognitive states are associated with late-day focus outcomes within a 26-day self-tracking framework. The findings suggest that early focus and tiredness were not strong indicators of later performance. Unexpectedly, early distraction and non-work screen use demonstrated positive associations with late-day focus. These results challenge simplified assumptions regarding productivity momentum and digital distraction.

While limited in scope, the results highlight the dynamic, state-dependent nature of productivity. By addressing the Trait vs. State gap and examining naturalistic behaviors within daily blocks, this project contributes a nuanced perspective to existing behavioral research. Although limited in scope, these findings suggest that productivity may operate as a dynamic, context-sensitive state rather than a stable daily trajectory, reinforcing the value of within-person analysis in behavioral research.

VI. Conclusions

This final chapter synthesizes the insights gained from this 26-day personal informatics study, providing a data-informed answer to the research questions regarding the relationship between early-day behavior and late-day focus. By moving beyond generic productivity "rules" and analyzing naturalistic personal data, this study offers a personalized perspective on the dynamic nature of cognitive performance.

A. Key Findings of the Study

The primary objective of this research was to determine which early-day behavioral and cognitive factors are associated with late-day focus. The analysis revealed several counter-intuitive results that challenge the traditional "momentum" model of productivity:

- The Stimulation-Recovery Effect: The most significant finding was that early-day distraction ($\tau = 0.35, p = 0.03$) and non-work screen use ($d = 1.06, p = 0.021$) were the only variables that showed statistically significant associations with late-day focus.
- The Absence of Momentum: Contrary to the Progress Principle, early-day focus levels showed no significant correlation with later performance ($\tau = -0.13, p = 0.41$), suggesting that focus is not necessarily cumulative but may reset across daily blocks.
- Secondary Influencers: Conventional productivity drivers, such as caffeine consumption ($p = 0.248$), morning tiredness ($p = 0.40$), and the timing of work commencement ($p = 0.601$), did not serve as a reliable indicator of performance outcomes in this dataset.

B. Personal Insights and Self-Discovery

Analysis of this person's own data significantly altered their understanding of cognitive rhythm. Prior to the study, it was assumed that a "distracted" morning or slow start would be associated with a wasted day. However, the data revealed that early-day disengagement may serve as a form of "cognitive priming." Late-day performance appears to be supported, rather than hindered, by initial periods of mental stimulation - even when that stimulation comes from non-work screens or general distraction. These findings suggest that focus is dynamically regulated throughout the day, rather than being a fixed trait determined solely by the first hour of work.

C. Real-Life Applications

The findings from this study suggest several practical adjustments to daily life and self-regulation:

- Strategic Disengagement: Instead of forcing "deep work" during low-energy mornings, this person can strategically use non-work screens or "distracted" leisure time as a transitional phase to build arousal for later tasks.
- Reducing "Linear Expectations": Understanding that focus resets between blocks allows for greater flexibility. If a morning block is unproductive, the afternoon can be treated as a fresh start rather than a continuation of a "bad" day.
- Data-Driven Personalization: The study reinforces the value of personal informatics. Because the observed results contradict general productivity advice, it highlights the importance of following individualized data over generic "best practices."

D. Final Conclusion

This study concludes that for this individual, late-day focus is not a result of early-morning momentum but is instead significantly associated with early-day mental stimulation and recovery-based disengagement. The positive relationship between distraction, screen use, and later performance provides preliminary support for the Effort-Recovery Model, suggesting that "distractions" can function as essential mental resets.

Ultimately, productivity does not follow a linear path of constant effort. It is a dynamic, context-sensitive state that benefits from a balance of intense focus and strategic disengagement. By acknowledging this nuance, this person can better align daily habits with observed cognitive patterns, moving away from rigid expectations and toward a more effective, data-informed approach to self-regulation.

REFERENCES

[1] M. Sonnentag, "Dynamics of well-being," Annual Review of Organizational Psychology and Organizational Behavior, vol. 2, pp. 261–293, 2015.

[2] T. M. Amabile and S. J. Kramer, "The progress principle: Using small wins to ignite joy, engagement, and creativity at work," Harvard Business Review Press, 2011. .

[3] S. Sonnentag and C. Fritz, "The recovery experience questionnaire: Development and validation of a measure for assessing recuperation and unwinding from work," Journal of Occupational Health Psychology, vol. 12, no. 3, pp. 204–221, 2007.

[4] J. P. Trougakos, S. G. Hideg, C. Cheng, and M. Beal, "Lunch breaks unpacked: The role of autonomy as a moderator of recovery during lunch," , vol. 57, no. 2, pp. 405–421, 2014.

[5] R. Larson and M. Csikszentmihalyi, "The experience sampling method," New Directions for Methodology of Social Behavioral Science, 1983.

[6] Tice, D. M., Baumeister, R. F. (1997). Longitudinal study of procrastination, performance, stress, and health. Psychological Science.

[7] Di Nocera, F., et al. (2023). A Lack of Focus, Not Task Avoidance, Makes the Difference: Work Routines in Procrastinators and Non-Procrastinators. Behavioral Sciences.

[8] Albulescu, P., et al. (2022). "Give me a break!" A systematic review and meta-analysis on the efficacy of micro-breaks. PLOS ONE.

[9] Choi, J., et al. (2017). Experience sampling method in productivity research. Frontiers in Psychology.