A Self-Tracked Analysis of Late-Night Resistance Training and Daily Productivity: The Role of Intensity and Behavioral Factors

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***Abstract*—Understanding how everyday behavioral patterns influence cognitive performance has become increasingly relevant in modern digital lifestyles characterized by high screen exposure, flexible schedules, and irregular sleep habits. This study investigates the relationship between late-night resistance training and next-day productivity using a quantified-self framework. Over a continuous 60-day period, daily information regarding workout participation, perceived intensity, sleep duration, screen time, and subjective productivity ratings was systematically recorded.**

Descriptive statistics, exploratory data analysis, Pearson correlation, independent t-tests, and multiple linear regression were applied to evaluate associations among variables. Results indicate that workout participation and higher perceived intensity are positively associated with improved next-day productivity. In contrast, increased screen exposure demonstrates a negative relationship. Sleep duration showed weaker and less consistent effects, potentially due to limited variability within the sample.

The regression model explained approximately 21.9% of the variance in productivity, suggesting that while exercise and digital behaviors contribute meaningfully, additional unmeasured factors such as psychological state or task demands also play a role. These findings highlight the value of personal behavioral analytics in identifying actionable insights for lifestyle optimization.

***Index Terms*—Quantified Self, Resistance Training, Productivity Analytics, Sleep Behavior, Screen Exposure, Behavioral Modeling, Personal Informatics.**

I. Introduction

A. Background

Daily productivity is shaped by a complex interaction of physical, psychological, and environmental factors. With the widespread adoption of digital devices and increasing academic and professional demands, individuals often struggle to balance exercise, rest, and cognitive performance. As a result, there is growing interest in understanding how everyday habits influence next-day functioning.

The quantified-self movement has enabled individuals to systematically monitor their own behaviors, offering opportunities to uncover patterns that may otherwise remain unnoticed. By leveraging routine data collection, people can explore relationships between lifestyle choices and performance outcomes in naturalistic settings.

Physical activity has been widely associated with benefits in mood, energy, and executive function. However, much of the literature focuses on daytime exercise, while late-night resistance training remains comparatively under-examined. For many students and working adults, evening hours represent the only feasible training window. Therefore, understanding whether workouts performed between 9 PM and 11 PM enhance or impair next-day productivity becomes practically important.

Simultaneously, screen time has emerged as a major behavioral factor affecting sleep and cognitive clarity. Excessive digital exposure may delay recovery, contribute to fatigue, and reduce attentional capacity.

This study integrates these domains by examining how late-night resistance training, sleep duration, and screen exposure interact to influence next-day productivity in a longitudinal self-tracked environment.

Beyond general associations, the interaction between exercise timing and digital behavior presents a particularly relevant modern challenge. Many individuals schedule workouts late in the evening due to academic or occupational responsibilities. While exercise is known to enhance physiological readiness and mood, late sessions may also influence arousal and sleep latency. At the same time, screen exposure frequently extends into nighttime hours, potentially compounding recovery challenges. Understanding how these overlapping behaviors affect productivity requires longitudinal, fine-grained observation rather than one-time laboratory measurement.

B. Problem Statement

This research investigates whether late-night resistance training enhances or impairs next-day productivity and evaluates how sleep duration and screen exposure interact with this relationship. By examining naturally occurring daily variations, the study aims to generate insights into personalized behavior optimization and the practical application of data-driven self-monitoring.

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C. Objectives

1) Collect and document non-sensitive self-tracked data over a two-month period.
2) Identify patterns between exercise variables and productivity outcomes. screen time, and productivity.
3) Determine whether productivity differs significantly between workout and rest days.
4) Quantify the relative influence of workout participation, intensity, sleep, and screen exposure through regression modeling.

D. Scope and Limitaion

- Only non-sensitive self-reported data were collected.
- The study period covers 60 consecutive days and involves a single participant, limiting generalizability.
- Factors such as stress, diet, and caffeine intake were not included.
- Findings are exploratory and intended to guide further research on personalized exercise and productivity tracking.

E. Research Hypotheses

To formally guide the statistical analysis and ensure objective testing of behavioral relationships, the following hypotheses were established.

1) Correlation Hypotheses: **Null hypothesis (H_{0_1}):** There is no significant linear relationship between perceived workout intensity, sleep duration, screen time, and next-day productivity ($r = 0$).

Alternative hypothesis (H_{1_1}): At least one variable (perceived intensity, sleep duration, or screen time) has a significant linear relationship with next-day productivity ($r \neq 0$).

2) Workout Participation Hypotheses (Independent t-test): **Null hypothesis (H_{0_2}):** There is no significant difference in mean productivity between workout days and rest days ($\mu_{workout} = \mu_{rest}$).

Alternative hypothesis (H_{1_2}): There is a significant difference in mean productivity between workout days and rest days ($\mu_{workout} \neq \mu_{rest}$).

II. Related Work

A. Self-Tracking and Behavioral Analytics

Quantified-self research emphasizes the value of personalized data collection for behavior improvement [6]. Context-aware self-tracking systems have been used to monitor multiple domains simultaneously, including physical activity, sleep, and digital engagement, providing insights into daily patterns and behavioral trends [7].

Lifelogging studies have shown that changes in sleep quality strongly influence cognitive performance, including alertness, task efficiency, and decision-making [8]. These findings demonstrate the relevance of tracking both behavioral and physiological variables when examining productivity outcomes.

B. Exercise, Sleep, and Cognitive Performance

Physical activity has consistently been linked to enhanced cognitive function and productivity. Regular exercise improves executive function, memory, and mood, which are critical for daily performance [3][4].

Late-night exercise may reduce sleep duration or alter sleep architecture, potentially impacting next-day alertness and task performance [9]. However, the extent to which exercise intensity interacts with sleep and productivity remains an open question, particularly in self-tracked, real-world datasets.

C. Screen Time and Sleep

Excessive screen exposure, particularly before bedtime, has been linked to delayed sleep onset, reduced sleep quality, and diminished next-day cognitive performance [5][10]. Understanding how screen time interacts with exercise habits can inform behavior recommendations aimed at optimizing productivity.

D. Gaps in Current Literature

While prior work has explored exercise, sleep, and productivity, few studies examine late-night resistance training combined with behavioral tracking in a self-tracked, longitudinal framework. This study contributes by integrating exercise, sleep, and digital behavior into a single analytical framework.

III. Methodology

A. Data Collection

Daily self-tracked data were collected over 60 consecutive days, including:

- **Workout variables:** workout_day, workout_type (Push/Pull/Legs) workout_duration (minutes) and perceived_intensity (1–10 scale).
- **Lifestyle variables:** sleep_duration (hours) and screen_time (hours).
- **Outcome variable:** productivity_score (1–5 scale).

No personally identifiable information or sensitive health data were collected.

B. Data Preprocessing

The dataset was examined for completeness, formatting consistency, and abnormal values. No missing entries were detected across the observation period. Dates were converted to datetime format and sorted chronologically. Visual inspection of distributions did not reveal extreme outliers requiring removal.

Because the goal of the study was to preserve real-world variability, minimal transformation was applied prior to analysis.

- Dataset verified for missing values — none found.
- Date field converted to datetime format.
- Outliers were visually inspected; no extreme values required removal.
- Variables were standardized for regression analysis.

TABLE I: Descriptive Statistics of Productivity Dataset

	date	w_day	w_dur	perceived intensity	sleep duration	screen time	prod score	rolling prod
count	60	60	60	60	60	60	60	54
mean	2025-12-30 12:00	0.7333	72.27	5.90	6.75	9.86	3.45	3.4524
min	2025-12-01 00:00	0	0	0	6.0	0.4	3.0	3.2857
25%	2025-12-15 18:00	0	0	0	6.2	9.15	3.0	3.4286
50%	2025-12-30 12:00	1	88	7	6.6	9.8	3.0	3.4286
75%	2026-01-14 06:00	1	116.25	9	7.5	10.73	4.0	3.5714
max	2026-01-29 00:00	1	140	9	7.9	12.9	4.0	3.7143
std	-	0.4460	50.4377	3.6671	0.6250	1.7011	0.5017	0.1352

C. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was conducted to understand general behavioral patterns before performing statistical testing. Time-series visualization revealed frequent daily fluctuations in productivity, primarily alternating between ratings of three and four. To highlight longer-term tendencies, smoothed representations were examined, which indicated relatively stable baseline functioning.

Continuous variables such as intensity, sleep duration, and screen time were also visualized against productivity to identify potential directional relationships. These exploratory steps provided intuitive grounding for subsequent inferential analysis.

- Descriptive statistics: Mean, min, max, and standard deviation calculated for all variables.
- Line plots: Showed fluctuations in exercise intensity, sleep, screen time, and productivity over 60 days.
- Bar charts: Revealed relationships among perceived intensity, sleep, screen time, and productivity.

D. Statistical Tests

- Pearson correlation measured linear relationships between variables.
- Independent t-test compared productivity on workout versus rest days.

Pearson correlation was used to evaluate linear associations between continuous contributors (perceived intensity, sleep duration, and screen time) and productivity. An independent samples t-test (t-test) compared mean productivity between workout days and rest days. Multiple linear regression modeled productivity using workout participation, perceived intensity, sleep duration, and screen time as contributors.

All hypothesis tests applied a significance level of 0.05. For each test, if the p-value was less than 0.05, the corresponding null hypothesis was rejected; otherwise, the null hypothesis was not rejected.

E. Regression Model

- Multiple linear regression modeled productivity as a function of perceived intensity, sleep duration, and screen time:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \qquad (1)$$

- (R^2) assessed how much variability in productivity the model explains.

TABLE II: Descriptive Statistics of Study Variables

Metric	**Mean**	**Min**	**Max**
Workout Day	0.73	0	1
Workout Duration (min)	72.27	0	140
Perceived Intensity	5.90	0	9
Sleep Duration (hr)	6.75	6	7.9
Screen Time (hr)	9.86	0.4	12.9
Productivity Score	3.45	3	4

IV. Results

A. Descriptive Statistics

Across the 60-day period, workouts occurred on approximately 73% of days. The average perceived intensity was 5.9, indicating moderate training effort. Mean sleep duration was 6.75 hours, slightly below common adult recommendations. Screen exposure averaged 9.86 hours per day, reflecting substantial interaction with digital devices.

Productivity values remained within a relatively narrow range, with a mean of 3.45. Despite this limited spread, statistical analysis revealed meaningful associations with behavioral variables.

- Workouts were moderately intense.
- Sleep slightly below adult recommendations (7–9 hrs).
- Screen time generally high (10 hr/day).

B. Productivity Over Time

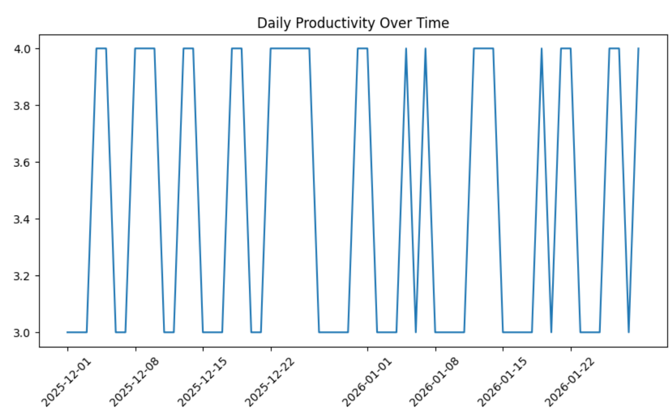

Fig. 1: Daily productivity scores across the 60-day period.

Figure 1 illustrates day-to-day productivity variation. Although frequent oscillations are observed, the absence of long-term decline suggests that late-night training routines did not produce cumulative fatigue. Instead, productivity remained stable, supporting the feasibility of maintaining evening workouts without major performance deterioration.

C. Correlation Analysis

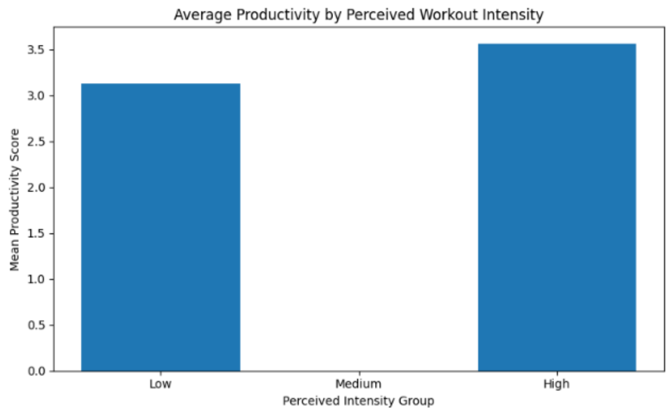

Fig. 2: Perceived workout intensity versus productivity score.

1) Intensity and Productivity: As shown in Figure 2, higher intensity levels tend to correspond with higher productivity outcomes. Pearson correlation confirmed a moderate positive association ($r = 0.39$, $p = 0.0019$). This indicates that increased exertion during training may enhance motivational or physiological readiness the following day.

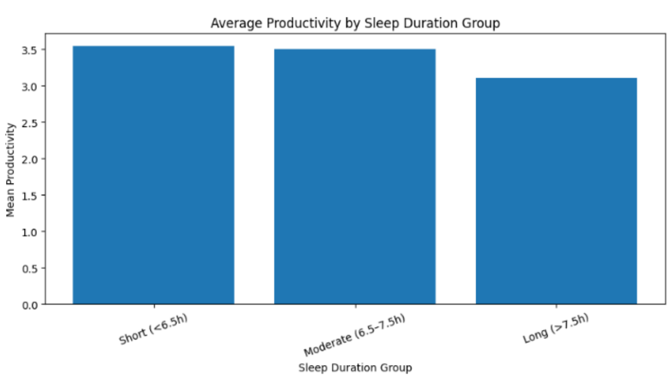

Fig. 3: Sleep duration versus productivity score.

2) Sleep Duration and Productivity: Figure 3 demonstrates relatively modest separation between productivity levels across sleep durations. Statistical analysis revealed a weak negative correlation ($r = -0.31$, $p = 0.0177$). One possible explanation is that sleep values varied within a restricted range, limiting detectable influence.

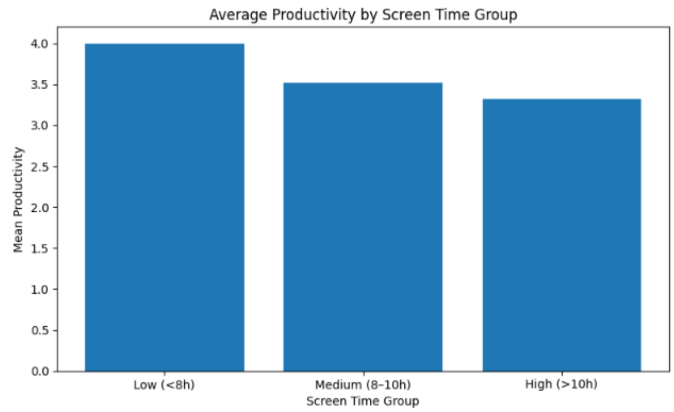

Fig. 4: Screen time versus productivity score.

3) Screen Exposure and Productivity: Higher digital exposure appears associated with lower productivity in Figure 5. The correlation was weak but statistically significant ($r = -0.31$, $p = 0.0169$). This aligns with theories of attentional fatigue resulting from prolonged device interaction.

TABLE III: Pearson Correlation Between Lifestyle Factors and Productivity

Variable	r	p-value
Sleep Duration	-0.305	0.018
Workout Intensity	0.393	0.002
Screen Time	-0.307	0.017

4) Summary of Correlation Results: Table III summarizes the Pearson correlation coefficients between behavioral variables and productivity. Perceived workout intensity demonstrated the strongest association ($r = 0.393$), while sleep duration and screen time showed weaker negative relationships.

Although sleep and screen exposure were statistically significant, their magnitudes were comparatively smaller. These findings support further multivariate modeling to evaluate the independent contribution of each variable.

D. Workout Versus Rest Days

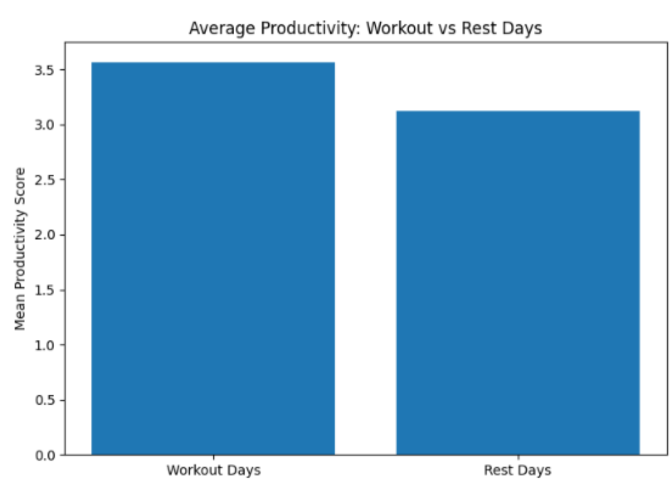

Fig. 5: Workout versus Rest Days.

TABLE IV: Independent Samples t-Test: Workout vs. Rest Days

Comparison	t-statistic	df	p-value
Workout vs. Rest	3.887	39.27	0.00038

An independent t-test comparing workout and rest days yielded a highly significant difference ($p = 0.00038$). Productivity was consistently higher following exercise. This finding suggests that even participation alone, independent of intensity magnitude, may confer cognitive or motivational benefits.

E. Regression Modeling

TABLE V: Multiple Linear Regression Results for Productivity

Variable	Coefficient (β)
Intercept	1.531
Workout Day	0.255
Intensity	0.061
Sleep Duration	0.303
Screen Time	-0.068
R^2	0.219

Multiple linear regression was applied to evaluate contributors simultaneously. Workout participation (+0.25) and perceived intensity (+0.06) demonstrated positive contributions. Sleep duration also showed a positive coefficient (+0.30), whereas screen exposure exhibited a negative effect (-0.068).

The model achieved an R^2 value of 0.219, indicating that approximately 22% of productivity variability can be explained by these measurable behaviors.

F. Correlation Matrix Visualization

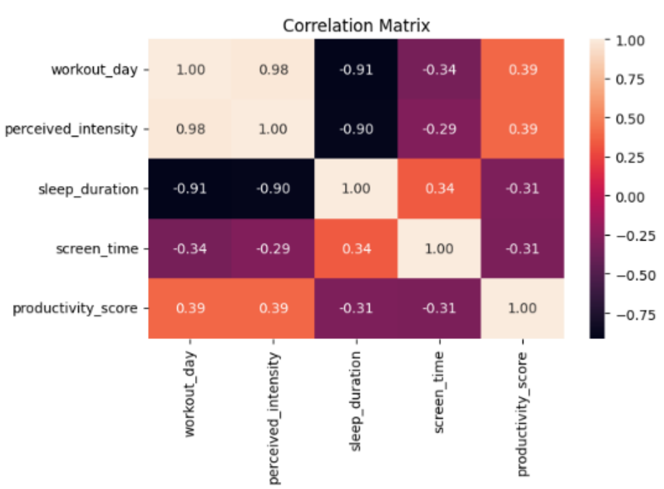

Fig. 6: Correlation matrix heatmap of behavioral and workout variables.

Figure 6 presents the Pearson correlation matrix among all recorded variables. The visualization confirms the moderate positive relationship between workout participation, perceived intensity, and productivity.

A noticeable negative association is observed between sleep duration and workout variables, suggesting that late-night training may slightly reduce total sleep hours. Screen exposure also shows a negative relationship with productivity.

The heatmap provides a comprehensive overview of variable interrelationships and supports the individual correlation results discussed earlier. Notably, no extreme multicollinearity is observed among the contributors, indicating that regression modeling remains appropriate.

V. Discussion

The findings of this study provide empirical support for the positive association between physical exercise and cognitive performance reported in prior research [3], [4]. In the present dataset, perceived workout intensity demonstrated a statistically significant moderate positive correlation with productivity ($r = 0.39$, $p = 0.0019$). This suggests that greater exertion during late-night resistance training is associated with improved next-day performance. Notably, regression analysis further confirmed that both workout participation and intensity contributed positively to productivity when controlling for other variables.

These results indicate that late-night resistance training does not appear to impair next-day functioning within this observation period. Despite concerns that evening exercise may reduce sleep duration, the data suggest that the motivational and physiological benefits of exercise may offset potential recovery limitations.

Screen exposure exhibited a statistically significant negative association with productivity ($r = -0.31$, $p = 0.0169$). This aligns with literature indicating that prolonged digital engagement may contribute to attentional fatigue and diminished cognitive clarity [**?**]. The regression coefficient for screen time further supports this relationship, indicating a consistent negative contribution even when other variables are controlled.

Sleep duration presented a more complex pattern. While simple correlation analysis showed a weak negative association, regression modeling revealed a positive coefficient when other variables were held constant. This suggests potential interaction effects among exercise, recovery, and digital exposure. Sleep duration alone may not fully capture sleep quality, timing, or efficiency, which could explain the mixed statistical outcomes.

The regression model explained approximately 22% of the variability in productivity ($R^2 = 0.219$). Although moderate, this level of explanatory power is consistent with behavioral research, where human performance is influenced by multiple interacting factors. The findings demonstrate that measurable lifestyle behaviors account for a meaningful portion of daily productivity fluctuations, while additional unobserved variables such as stress, workload, or emotional state likely contribute to remaining variance.

Overall, the study illustrates the feasibility and value of self-tracked behavioral analytics in understanding short-term performance dynamics.

VI. Conclusion and Future Work

This study demonstrates that late-night resistance training intensity is positively associated with next-day productivity within a 60-day self-tracked dataset. Statistical findings led to the rejection of all null hypotheses at the 0.05 significance level, indicating that meaningful relationships exist between behavioral variables and productivity outcomes. Workout participation and perceived exertion emerged as significant contributors to improved performance, while higher screen exposure was consistently associated with reduced productivity. Sleep duration displayed a more nuanced relationship, suggesting that recovery quality may require more precise measurement beyond duration alone.

Although the regression model explains a moderate proportion of productivity variance, the results highlight the practical relevance of exercise behavior and digital exposure management in daily performance optimization. The quantified-self approach demonstrated in this study provides a scalable framework for individuals seeking data-driven, evidence-based lifestyle adjustments.

Future research should expand the sample size, incorporate wearable monitoring technologies for objective measurement, and examine additional behavioral and physiological variables such as stress levels, caffeine intake, workload intensity, and circadian timing. Comparative analysis between morning and late-night exercise sessions may also provide further insight into optimal training schedules for cognitive performance.

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