Understanding Daily Behavioral Patterns of Working Students through Exploratory Data Analysis: A Quantified Self Case Study

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Abstract. This study examines daily behavioral patterns of a working student in Metro Manila over 89 days through structured self-tracking and their relationship to mood and focus. Data were collected via Google Sheets daily logs and analyzed using exploratory data analysis and inferential statistics. Variables included sleep, work/study hours, distraction time, travel time, tasks completed, and 5-point Likert scales for mood and focus. Three hypotheses were tested: (1) Recovery vs. Inertia—whether rest days precede deep work or sustained low performance; (2) Busywork vs. Flow State—whether high-volume days can be distinguished by focus ratings; and (3) Weekend Bleed—whether work intrudes into weekends and impacts mood. Results revealed a strong mood-focus correlation ($r = 0.62$, $p < 0.05$). Transition analysis supported inertia over recovery: zero rest days (0/9) preceded deep work, while 44.4% led to continued low performance. Among 45 high-volume days, focus significantly discriminated Busywork ($M = 1.73$) from Flow State ($M = 3.93$; $t = -9.82$, $p < 0.001$). Work/study patterns appeared on 34.6% of weekends without significant calendar association ($\chi^2 = 1.98$, $p = 0.12$); surprisingly, weekend work days showed higher mood ($M = 3.50$) than weekend rest days ($M = 2.80$). Findings demonstrate that unstructured rest does not predict next-day productivity, focus quality distinguishes productive from merely busy days, and weekend work may not harm well-being for intrinsically motivated students. This research illustrates how quantified self-methods transform behavioral intuitions into testable hypotheses and actionable insights for working students managing dual academic-professional demands.

Keywords: Quantified Self · Working Students · Exploratory Data Analysis · Self-Tracking · Behavioral Patterns · Productivity Analysis · Flow State · Recovery · Inertia · Weekend Bleed

1 Introduction

1.1 Background of the Study

In the contemporary landscape of pervasive computing, the "Quantified Self" (QS) movement has transitioned from a niche hobby to a rigorous method of self-knowledge through data, enabling individuals to treat "The Day" as a distinct, measurable data point [1]. For working students in high-density urban environments like Metro Manila, daily life represents a complex optimization problem where time is a scarce resource divided among professional output, academic deadlines, travel time, and the physiological necessity of rest. While students often rely on intuition to gauge their productivity, such perceptions are frequently flawed; a day characterized by high screen time may feel "busy" but result in low output, whereas a day of rest might be perceived as "lazy" but actually serve as a critical recovery mechanism. By aggregating consistent, self-reported daily logs using manual input, this study aims to move beyond flawed intuition toward an objective, evidence-based understanding of how daily behaviors relate to cognitive performance and well-being.

Previous research in the domain of educational data mining, such as the SmartGPA and StudentLife studies, has indicated that significant correlations exist between lifestyle factors—including sleep patterns, socialization, and study duration—and a student's academic success. These studies have shown that behavioral features like increased time at academic facilities and decreased location variation are strong indicators of higher academic performance [2]. Furthermore, personality traits such as conscientiousness have been identified as long-term indicators of higher-grade point averages [3]. This study builds upon these established frameworks by applying exploratory data analysis and inferential statistics to a single-subject dataset, specifically investigating the nuances of the working student profile in a modern "Big Data" era.

1.2 Problem Statement and Research Questions

Despite the wealth of data provided by modern technology, there remains a critical ambiguity in how students distinguish between high-volume "Busywork" and true "Flow States," as raw work hours often fail to account for subjective focus and cognitive depth. This research addresses the "Recovery vs. Inertia" paradox, questioning whether periods of rest effectively prime a student for subsequent "Deep Work" or if unstructured downtime instead precipitates a continued state of low performance. Additionally, the study explores the "Weekend Bleed" effect, analyzing the extent to which professional and academic obligations intrude into weekends and how this permeability of work-life boundaries influences self-reported mood and focus. The overarching goal is to identify the patterns existing in daily inputs—such as music genre, travel time, and distraction—to determine their precise relationship with a student's ability to maintain high-focus productivity profiles.

What patterns exist in daily inputs (music genre, sleep, travel time) and behaviors (work hours, study hours, distraction time), and how do these patterns relate to self-reported mood and focus? First, Recovery vs. Inertia Hypothesis: Do "Rest Profiles" (High

Leisure, Low Productivity) typically precede "Deep Work" patterns (suggesting recovery), or do they precede further low-performance patterns (suggesting inertia)? Second, Busy vs. Productive Distinction: Can data analysis distinguish between "High-Volume / Low-Focus" days (Busywork) and "High-Volume / High-Focus" days (Flow State) based on the relationship between Work Hours and Distraction Time? Lastly, Weekend Bleed Effect: Do specific habit patterns strictly align with calendar weekends, or do "Work/Study" patterns significantly intrude into weekends, and is this intrusion associated with "Low Mood" outcomes?

Despite the wealth of data provided by modern technology, there remains a critical ambiguity in how students distinguish between high-volume "Busywork" and true "Flow States," as raw work hours often fail to account for subjective focus and cognitive depth. This research addresses the "Recovery vs. Inertia" paradox, questioning whether periods of rest effectively prime a student for subsequent "Deep Work" or if unstructured downtime instead sequences into a continued state of low performance. Additionally, the study explores the "Weekend Bleed" effect, analyzing the temporal predictability of professional and academic obligations intruding into weekends, and how this permeability of work-life boundaries influences self-reported mood. The overarching goal is to identify the patterns existing in daily inputs—such as travel time, distraction, and sleep—to determine their precise statistical relationship with a student's ability to maintain high-focus productivity profiles.

Specifically, this study aims to answer the following research questions: What patterns exist in daily inputs and behaviors, and how do these temporal patterns relate to self-reported mood and focus?

- **First, Recovery vs. Inertia Hypothesis:** Do "Rest Profiles" typically precede "Deep Work" patterns (suggesting a cyclical recovery), or do they sequence into further low-performance patterns (suggesting inertia) when analyzed sequentially over time?

- **Second, Busy vs. Productive Distinction:** Can statistical analysis differentiate between "Busywork" (High-Volume / Low-Focus) and "Flow State" (High-Volume / High-Focus) days by contrasting absolute work duration against non-parametric subjective focus ratings?

- **Lastly, Weekend Bleed Effect:** Do "Work/Study" patterns exhibit a predictable, stationary alignment with calendar weekends, or do they irregularly intrude into weekends, and is this unpredictable intrusion associated with negative mood outcomes?

1.3 Hypothesis and Statistical Framework

To ensure methodological rigor, this study employs statistical methods calibrated to the specific data distributions and sample sizes. Time series modeling (Augmented Dickey-Fuller testing) is utilized to evaluate temporal dependencies, while non-parametric tests (Mann-Whitney U) are applied to ordinal subjective metrics, moving beyond traditional parametric constraints.

1. H1 (Recovery vs. Inertia): Rest days do not exhibit stationary recovery patterns over time but rather sequence into continued low-performance states (inertia). H0: Rest days are not significant predictors of "Deep Work" days the following day; the transition sequence is non-stationary and random. Ha: Rest days are significant predictors of "Deep Work" days the following day; the transition sequence follows a predictable, stationary recovery pattern.

2. H2 (Busywork vs. Flow State): While absolute work volume (Work_Hours) does not statistically differentiate high-volume days, subjective focus (Focus_Rating) significantly discriminates between "Flow State" and "Busywork." H0: There is no significant difference in absolute work volume (*Work_Hours*) and subjective focus (*Focus_Rating*) between high-volume "Busywork" and "Flow State" days. Ha: There is a significant difference in subjective focus (*Focus_Rating*) between "Busywork" and "Flow State" days, even if absolute work volume remains statistically similar.

3. H3 (Weekend Bleed Effect): Work and study patterns intrude into weekends without exhibiting stationary, predictable calendar dependency, yet this intrusion does not negatively impact overall mood. H0: The intrusion of study/work patterns into the weekend (Weekend Bleed) does not follow a predictable time-series pattern, and there is no significant difference in mood between working and resting on weekends. Ha: The intrusion of study/work patterns into the weekend follows a predictable time-series pattern and significantly affects the subsequent mood of the student.

1.4 Significance of the Study

This research contributes to the growing body of literature on educational data mining and personal informatics by examining the lived experience of working students through quantitative self-tracking methods. The findings may inform evidence-based strategies for time management, work-life balance optimization, and mental health maintenance among students who juggle multiple responsibilities. By identifying actionable patterns in daily behavior and their relationship to cognitive performance, this study provides a framework for students to move from intuitive self-assessment to data-driven decision-making about their schedules and habits. Furthermore, the single-subject design allows for deep, granular analysis that complements large-scale studies by capturing the individual variation and contextual nuances often lost in aggregate data. The insights gained from this research may benefit educational institutions in understanding the unique challenges faced by working students, potentially informing support services, scheduling policies, and wellness programs tailored to this demographic.

1.5 Scope and Limitations

This study focuses on a single working student's daily behavioral pattern over an extended period, tracked through self-reported logs. The analysis examines relationships between various lifestyle factors (sleep, work hours, study hours, leisure time, travel time, music listening habits) and self-reported outcomes (mood, focus, productivity).

The scope of this research encompasses the analysis of daily behavioral patterns and their correlates, with particular attention to the examination of weekday versus weekend patterns. The investigation delves into temporal sequences, such as whether rest days precede productive days, and explores the relationship between objective metrics derived subjective assessments of well-being. This approach allows for a comprehensive understanding of how different aspects of daily life interact and influence one another over time.

However, several limitations must be acknowledged. The single-subject design, while allowing for deep granular analysis, limits the generalizability of findings to broader populations. Self-reported data may be subject to recall bias or reporting inconsistencies, as participants may not always accurately remember or record their daily activities and emotional states. Additionally, this study examines correlations rather than establishing causal relationships between variables; observed associations do not necessarily imply that one factor directly causes changes in another. Context-specific factors unique to Metro Manila's urban environment, such as extreme traffic conditions and high population density, may not apply to other settings, potentially limiting the applicability of findings to students in different geographical contexts. Finally, the specific profile of a working student who maintains concurrent employment while pursuing academic studies may differ substantially from traditional full-time students who do not face the same dual demands on their time and cognitive resources.

2 Review of Related Literature

2.1 Quantified Self and Educational Data Mining

The integration of mobile sensing technologies with educational research has enabled unprecedented insights into student behavior and academic performance. The Quantified Self movement represents a paradigm shift from intuitive self-assessment to objective, data-driven understanding of personal behavior patterns. This approach has become particularly relevant in educational contexts, where researchers have begun to leverage smartphone and wearable technology to understand the complex interplay between student behaviors and academic outcomes [1].

The SmartGPA study pioneered the use of smartphone sensor data to predict and understand college student academic performance. This groundbreaking research demonstrated that behavioral features extracted from mobile devices could serve as reliable indicators of academic success. The study concluded that students who spend time at fraternities tend to perform more poorly academically, while students who socialize more at their dorms are more likely to have higher GPAs. Furthermore, the research correlated increasing conversation duration with higher GPA, which could indicate more group work and communication towards the end of the semester. The Lasso regression analysis employed in the SmartGPA study selected conscientiousness as the primary long-term indicator of higher-grade point average, suggesting that personality traits play a crucial role in academic outcomes [1].

Building upon this foundation, the StudentLife project further demonstrated that assessing mental health, academic performance, and behavioral trends through smartphones provides valuable insights into student well-being and success. This comprehensive study tracked college students throughout an entire semester, collecting data on physical activity, social interactions, study patterns, and mental health indicators. The findings revealed complex relationships between lifestyle factors and academic achievement that would be impossible to capture through traditional survey methods alone [2].

While these studies leveraged automated sensor data collection, alternative approaches using structured self-reporting have also proven valuable in understanding student behavior patterns. Self-reported daily logs offer certain advantages, including the ability to capture subjective states such as mood and focus that are difficult to infer from sensor data alone, as well as the capacity to record context-specific activities that automated systems may misclassify. This approach allows for intentional reflection on daily activities, potentially increasing participant awareness of their own behavioral patterns.

2.2 Lifestyle Factors and Academic Performance

Previous research has consistently indicated that correlations exist between lifestyle factors—such as study habits, study duration, socialization time, and campus involvement—and a student's academic success. These relationships extend beyond simple time allocation to encompass the quality and context of student activities, as well as their physical and mental health status.

One fundamental lifestyle factor is class attendance conducted research at the College of New Jersey that correlated higher attendance rates with higher GPA outcomes. Using a least-squares regression and a defined probability model, this study compared the number of missing classes with GPA and concluded that students who did not miss more than three classes per week were significantly more likely to achieve a GPA in the 3.1 to 4.0 range. This finding underscores the importance of consistent academic engagement as a predictor of success [3].

Mental health represents another critical dimension of student performance. Research has demonstrated that mental health significantly impacts academic success in college, with depression and anxiety showing consistent negative effects on performance, found that mental health conditions not only affect current academic performance but can also have lasting impacts on degree completion and career trajectories. The relationship between mental health and academic achievement appears to be bidirectional, with poor academic performance potentially exacerbating mental health challenges while mental health difficulties simultaneously undermine academic capabilities [4].

Personality traits constitute long-term predictors of academic outcomes that operate independently of immediate behavioral patterns. A study identified conscientiousness as strongly associated with higher college grade point averages. Conscientiousness, characterized by dutifulness, self-discipline, and achievement orientation, predicts academic success across diverse contexts and populations. This personality trait appears to influence not only the quantity of effort students invest in their studies but also the consistency and organization with which they approach academic tasks.

However, considerable research gaps remain regarding how significantly personality impacts academic success in comparison to environmental and behavioral factors [5].

Physical activity represents another lifestyle factor with documented relationships to academic performance. A study found that college student work habits are related to physical activity and fitness levels, suggesting that students who maintain regular physical exercise may develop time management and self-regulation skills that transfer to academic contexts [6]. Similarly, research demonstrated that physical activity correlates with higher GPAs among health science graduate students, with moderate levels of exercise associated with optimal academic outcomes [7]. These findings suggest that physical health and academic performance are not competing priorities but rather mutually reinforcing aspects of student success.

Stress constitutes a complex factor in academic achievement. While high levels of stress generally correlate with poorer academic outcomes, the relationship is not entirely linear. Elias et al. [8] examined stress and academic achievement among undergraduate students, finding that moderate stress can sometimes serve as a motivating factor, while excessive stress becomes debilitating [8]. The key appears to lie not in eliminating stress entirely but in developing effective coping mechanisms and maintaining stress at manageable levels.

Despite extensive research on individual lifestyle factors, significant gaps remain in our understanding of how these factors interact within the context of working students. Most existing studies focus on traditional full-time students who do not face the dual demands of concurrent employment and academic responsibilities. Working students must navigate additional constraints including limited time availability, competing professional obligations, and the cognitive load of context-switching between work and study roles. Understanding how lifestyle factors influence academic performance within this specific population requires targeted research that acknowledges these unique challenges.

3 Methodology

3.1 Participant and Data Collection

This study employed a single-subject design (n = 1) focusing on a working student residing in Metro Manila. The participant is a full-time professional concurrently enrolled in a Data Science program. Data collection spanned a duration of 89 days, commencing on November 19, 2025, and concluding on February 15, 2026. A structured daily logging instrument hosted on Google Sheets served as the primary data collection tool. Entries were recorded once daily at the conclusion of the day to ensure consistency. Participation in this study was voluntary, and the data is self-reported with full informed consent utilized for academic analysis

3.2 Variables and Operational Definitions

The study tracked a set of daily variables categorized into temporal allocation, performance output, and subjective well-being. Table 1 presents the primary variables and their operational definitions. Quantitative metrics included durations for sleep, professional work, academic study, and commuting, alongside a discrete count of completed tasks. Subjective states—specifically mood and focus—were assessed using a standard 5-point Likert scale ranging from 1 (Very Poor) to 5 (Excellent).

Beyond raw metrics, composite variables were synthesized to categorize daily performance profiles. A "Work/Study Profile" was defined as days where combined work and study hours exceeded the median. These high-volume days were further classified into "Flow State" (high focus) or "Busywork" (low focus) based on the median split of the Focus_Rating variable. Additionally, a "Weekend Bleed" indicator was derived to track the intrusion of high-workload profiles into Saturday and Sunday.

Table 1. List of variables used in analysis.

Feature Category	Feature
Sleep Hours	Duration of sleep previous night (hours)
Work Hours	Estimated professional work (hours)
Study Hours	Estimated academic study (hours)
Distraction Time Minutes	Time on social media, games, entertainment (minutes)
Travel Time Hours	Commute duration (hours)
Tasks Completed	Number of tasks accomplished (count)
Mood Rating	Self-reported mood 1-5 (very poor to excellent)
Focus Rating	Self-reported focus 1-5 (very poor to excellent)
Is Weekend	Saturday/Sunday (derived from date)

3.3 Data Preprocessing

The raw dataset underwent preprocessing using Python (Pandas library). Missing numeric values, which indicated a lack of activity (0 work hours on a rest day), were imputed with zero to preserve the integrity of mathematical operations. Categorical variables, such as "Mode of Transport" and "Music Genre," were transformed using one-hot encoding. Outliers identified through visual inspection (box plots) were retained, as they represented genuine behavioral variations—such as "crunch time" workdays—rather than measurement errors. Finally, continuous variables were standardized using Z-score normalization.

$$z = \frac{(x - \mu)}{\sigma}$$

3.4 Statistical Analysis Methods

3.4.1 Derived Variables and Operational Definitions

To support hypothesis testing, composite variables were synthesized to categorize daily performance profiles based on median splits of the dataset. The following operational definitions were applied:

Rest Day: A Day characterized by both Work_Hours < median AND Study_Hours < median AND Distraction_Time_Mins > median. This profile represents days with minimal productive activity and high leisure engagement.

Deep Work Day: A day where (Work_Hours + Study_Hours) > median AND Distraction_Time_Mins < median. This profile captures high productivity with minimal interruption.

High-Volume Day: Any day where (Work_Hours + Study_Hours) > median, regardless of distraction level.

Flow State: Among high-volume days, those with Focus_Rating > median (indicating high subjective engagement).

Busywork: Among high-volume days, those with Focus_Rating ≤ median (indicating low subjective engagement despite high time investment).

Work/Study Profile: Days where (Work_Hours + Study_Hours) > median, used to identify productive days.

Weekend Bleed: The occurrence of a Work/Study Profile on Saturday or Sunday, indicating intrusion of work patterns into weekends.

3.4.2 Descriptive and Exploratory Analysis

The analysis commenced with the calculation of measures of central tendency (mean, median) and dispersion (standard deviation, range) for all continuous variables. Time-series visualizations were generated to identify longitudinal trends and temporal patterns across the 89-day observation period. Distribution characteristics were assessed through histograms and box plots to detect skewness, bimodality, and outliers.

Pearson correlation matrices were generated to assess linear relationships between continuous variables (Sleep_Hours, Work_Hours, Study_Hours, Travel_Time_Hours, Distraction_Time_Mins, Tasks_Completed, Mood_Rating, Focus_Rating). Correlation coefficients (r) were tested for statistical significance at $\alpha = 0.05$ to identify meaningful pairwise associations that inform subsequent hypothesis testing.

Inferential analysis was adapted to the specific variable types. For continuous temporal variables, independent-samples t-tests were utilized. However, for ordinal subjective metrics, the non-parametric Mann-Whitney U test was employed to compare distributions without assuming normality. Furthermore, to analyze sequential behavioral patterns across the 89-day observation period, time series stationarity was evaluated. Due to the limited sample size of specific subset transitions precluding robust ARIMA modeling, the Augmented Dickey-Fuller (ADF) test was utilized as the primary alternative to assess the stationarity and temporal predictability of these habits.

3.4.3 Comparative Analysis: Weekday vs. Weekend

Inferential tests were conducted to compare distributions between weekday and weekend contexts. For continuous variables such as Work_Hours and Study_Hours, independent-samples t-tests were employed due to their robustness to unequal sample sizes (63 weekdays vs. 26 weekend days) and potential heterogeneity of variance. However, for ordinal subjective metrics like Mood_Rating and Focus_Rating, the non-parametric Mann-Whitney U test was applied to compare distributions without assuming normality. The test statistics (t or U), degrees of freedom (where applicable), and p-values were reported, with statistical significance determined at $\alpha = 0.05$. The null hypothesis for each test posited no difference between weekdays and weekends.

3.4.4 Hypothesis 1: Recovery vs. Inertia

To evaluate whether Rest Days facilitate subsequent productivity (Recovery Hypothesis) or perpetuate low performance (Inertia Hypothesis), a transition analysis was performed. For each of the identified Rest Days ($n = 9$), the profile of the immediately following day was classified as:

Rest → Deep Work (supporting Recovery)
Rest → Low Performance (supporting Inertia)
Rest → Other (moderate activity)

The conditional probability P(Deep Work | Previous Day = Rest Day)was calculated and compared to P(Low Performance | Previous Day = Rest Day). Furthermore, to determine if these transitions follow a predictable, cyclical recovery pattern rather than random occurrence, time series stationarity was evaluated using the Augmented Dickey-Fuller (ADF) test. Due to the limited sample size of specific subset transitions precluding robust ARIMA modeling, the ADF test served as the primary indicator of temporal predictability.

3.4.5 Hypothesis 2: Busywork vs. Flow State

To distinguish between high-volume work with low cognitive engagement (Busywork) versus high-volume work with high engagement (Flow State), all High-Volume Days were classified based on the median *Focus_Rating*. To validate this classification methodologically, two distinct tests were applied. An independent-samples t-test was used to compare the absolute time invested (*Work_Hours*) between the two states. Conversely, a non-parametric **Mann-Whitney U test** was applied to compare the ordinal *Focus_Rating* distributions. Statistical significance at $\alpha = 0.05$ for the non-parametric test would confirm that subjective focus, rather than raw time investment, robustly discriminates between these qualitatively different productivity modes.

3.4.6 Hypothesis 3: Weekend Bleed Effect

To assess whether professional and academic obligations intrude into weekends in a predictable, systematic pattern, time-series analysis was employed. Specifically, the Augmented Dickey-Fuller (ADF) **test** was conducted on the temporal sequence of "Weekend Bleed" occurrences (weekends exhibiting a Work/Study Profile). The null hypothesis posited that the series is non-stationary, meaning the intrusion of work into weekends happens irregularly rather than following a fixed calendar cycle. The ADF statistic and p-value were computed, with significance determined at $\alpha = 0.05$. Additionally, mean *Mood_Rating* was compared between "Weekend Bleed" days (weekends with Work/Study Profile) and "Weekend Rest" days (weekends without Work/Study Profile) using descriptive statistics to assess whether weekend work is empirically associated with reduced psychological well-being.

3.5 Environment and Tools

Table 2. Tools and description used in the whole environment

Tools	Version	Description
Python	3.9.25	Python version used in the analysis
Anaconda	2024.10.1	Python Environment
Pandas	2.3.3	Data manipulation and preprocessing
NumPy	2.0.2	Numerical computations
SciPy	1.13.1	Statistical tests
Seaborn	0.13.2	Data visualization
Matplotlib	3.9.4	Data visualization

4 Results

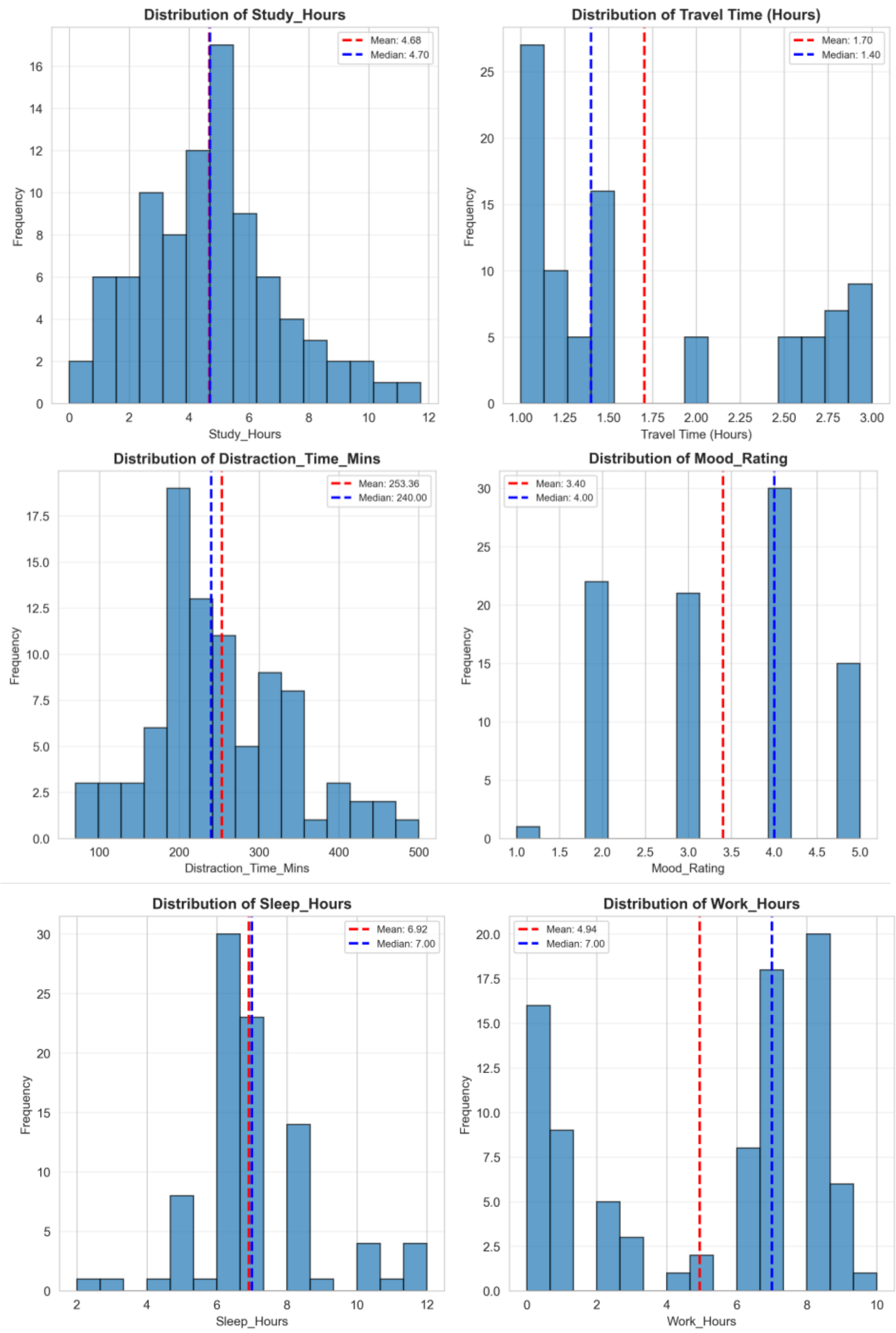
4.1 Descriptive Statistics and Dataset Characteristics

The final dataset consists of 89 consecutive daily observations (N=89) collected from November 19, 2025, to February 15, 2026, comprising 63 weekdays (70.8%) and 26 weekend days (29.2%). The data reveals substantial variability in sleep and productivity metrics. Sleep duration averaged 6.30 hours (SD = 2.69), but the range (0.00 – 12.00 hours) and the bimodal distribution observed in histograms suggest an inconsistent sleep schedule characterized by distinct periods of deprivation and recovery. Digital distraction was notably high, with a daily mean of 219.36 minutes (approximately 3.66 hours), and followed an approximately normal distribution. Conversely, Work Hours (M = 4.52) exhibited a right-skewed distribution, indicating that while many days involved minimal professional work, specific intensive days reached up to 10 hours. Subjective well-being metrics (Mood and Focus) averaged near the midpoint of the 5-point scale (M = 3.14 and M = 2.93, respectively), with mood displaying a bimodal distribution that implies distinct "good" and "poor" days rather than a consistent neutral state.

Table 3. Descriptive Statistics of Daily Logs (N = 89) of the selected variables.

Variable	Mean	Median (50%)	Std. Dev	Min	Max	Range
Sleep Hours	6.92	7	1.8	2	12	10
Work Hours	4.94	7	3.34	0	10	10
Study Hours	4.68	4.7	2.38	0	11.73	11.73
Travel Time (Hours)	1.7	1.4	0.73	1	3	2
Distraction Time (Mins)	253.36	240	85.14	70	500	430
Tasks Completed	3.82	3	1.87	0	10	10
Mood Rating (1-5)	3.4	4	1.07	1	5	4
Focus Rating (1-5)	3.28	3	1.24	1	5	4

Fig. 1. Distribution of daily behavioral variables (N = 89). Each panel shows the histogram for one variable; vertical lines indicate mean and median. Bimodal patterns appear in Sleep Hours and Mood Rating; Work Hours and Study Hours are right-skewed.



Distribution of Study_Hours
Mean: 4.68
Median: 4.70
Frequency
Study_Hours
Distribution of Travel Time (Hours)
Mean: 1.70
Median: 1.40
Frequency
Travel Time (Hours)
Distribution of Distraction_Time_Mins
Mean: 253.36
Median: 240.00
Frequency
Distraction_Time_Mins
Distribution of Mood_Rating
Mean: 3.40
Median: 4.00
Frequency
Mood_Rating
Distribution of Sleep_Hours
Mean: 6.92
Median: 7.00
Frequency
Sleep_Hours
Distribution of Work_Hours
Mean: 4.94
Median: 7.00
Frequency
Work_Hours

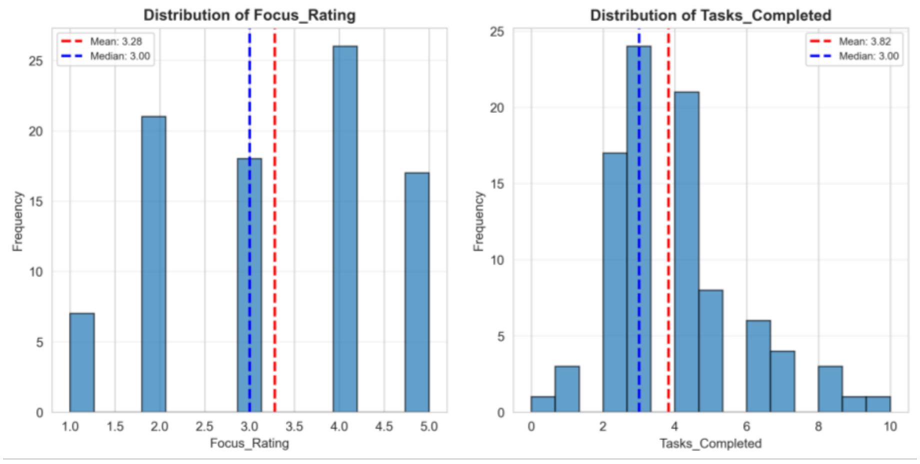
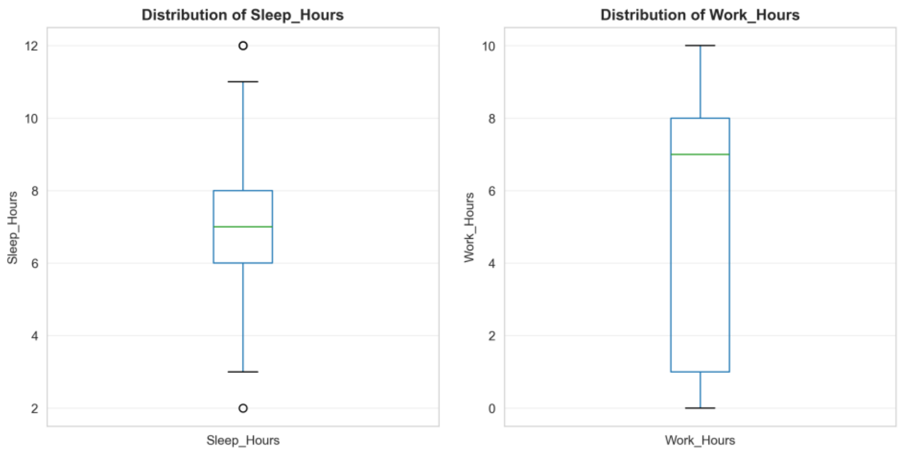
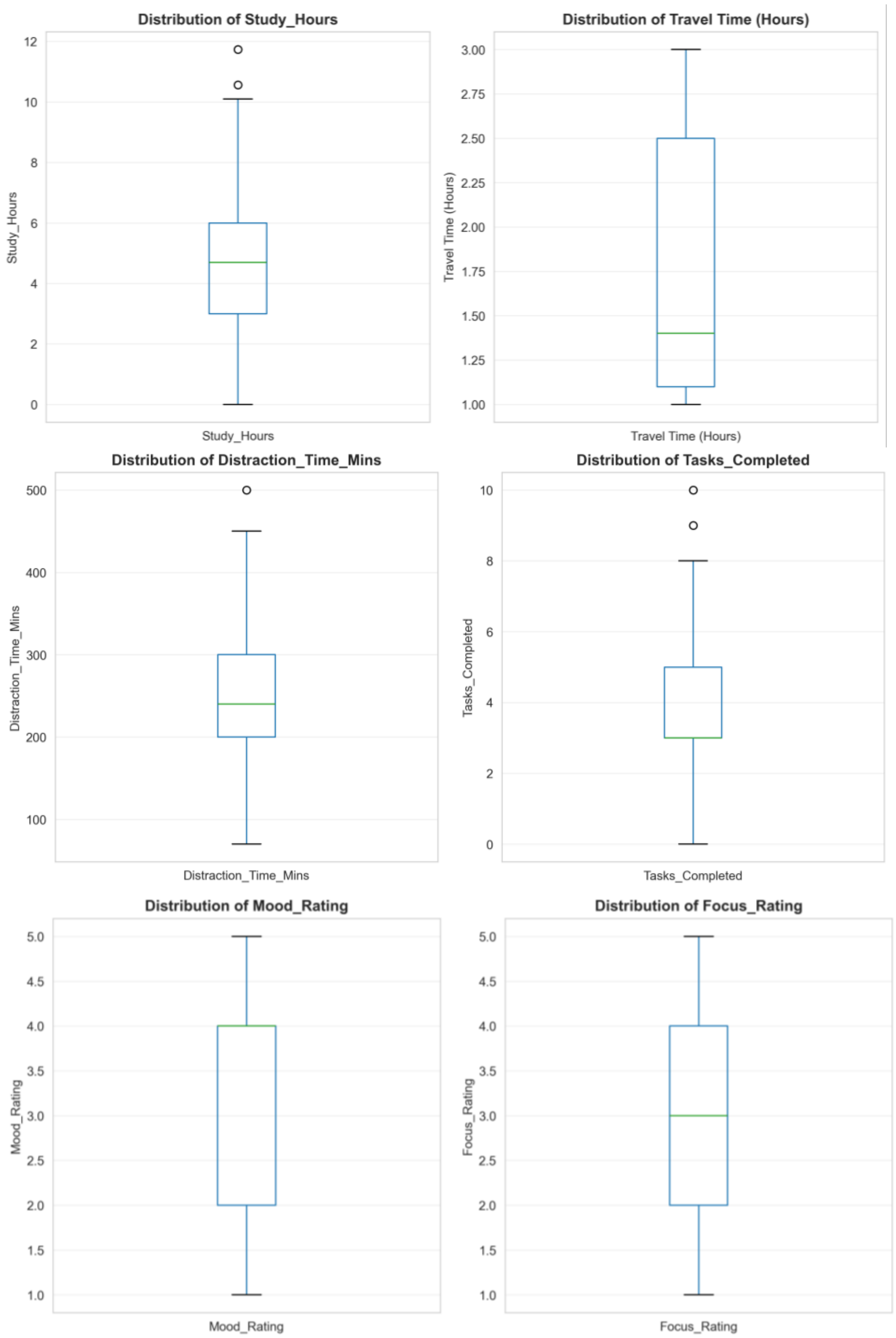


Fig. 2. Box plots of daily behavioral variables (N = 89). Boxes show interquartile range; the line inside is the median. Points outside the whiskers are outliers (0-h sleep days, intensive work/study days, high-distraction days) retained as genuine behavioral variation.



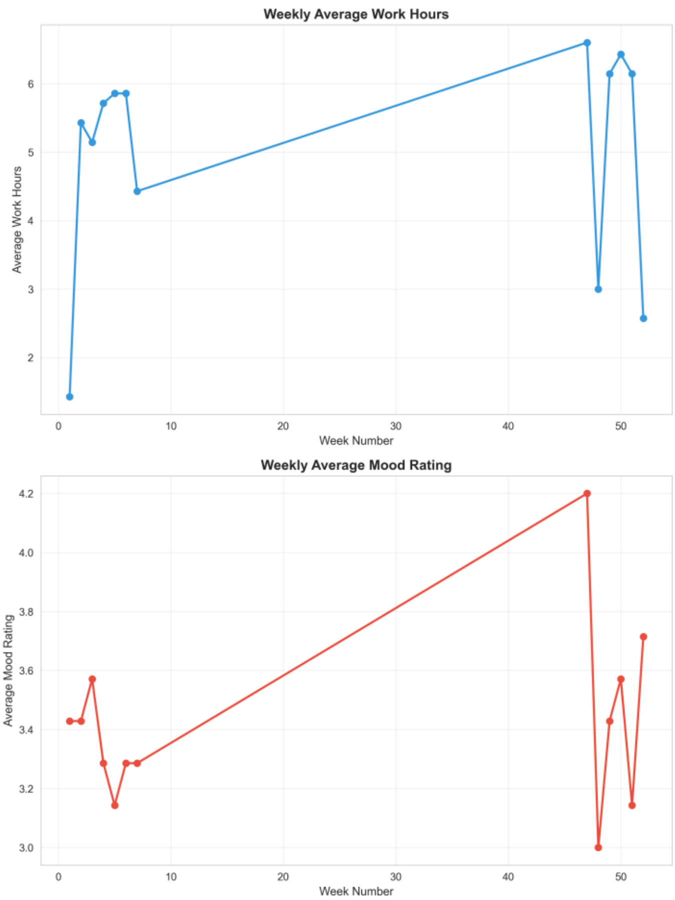

Distribution of Study_Hours
Study_Hours
0 2 4 6 8 10 12
Study_Hours
Distribution of Travel Time (Hours)
Travel Time (Hours)
1.00 1.25 1.50 1.75 2.00 2.25 2.50 2.75 3.00
Travel Time (Hours)
Distribution of Distraction_Time_Mins
Distraction_Time_Mins
100 200 300 400 500
Distraction_Time_Mins
Distribution of Tasks_Completed
Tasks_Completed
0 2 4 6 8 10
Tasks_Completed
Distribution of Mood_Rating
Mood_Rating
1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Mood_Rating
Distribution of Focus_Rating
Focus_Rating
1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Focus_Rating

4.2 Temporal and Comparative Analysis

Work Hours pronounced variability with several peaks exceeding 8 hours and valleys dropping to near zero. The pattern suggests irregular work intensity rather than consistent daily engagement. Study Hours exhibited similar volatility with notable peaks during certain weeks, likely corresponding to academic deadlines or exam periods.

Mood Rating fluctuated between ratings of 1 and 5 throughout the observation period, with clear periods of sustained low mood and periods of sustained high mood. Focus Rating displayed comparable patterns, often co-varying with Mood Rating, suggesting potential interdependence between affective and cognitive states.

Fig. 3. The panels illustrate the temporal fluctuations in Work Hours, Study Hours, Mood Rating, and Focus Rating over the 89-day observation period. The trends highlight significant volatility and distinct phases of high and low activity over the 89-day period.



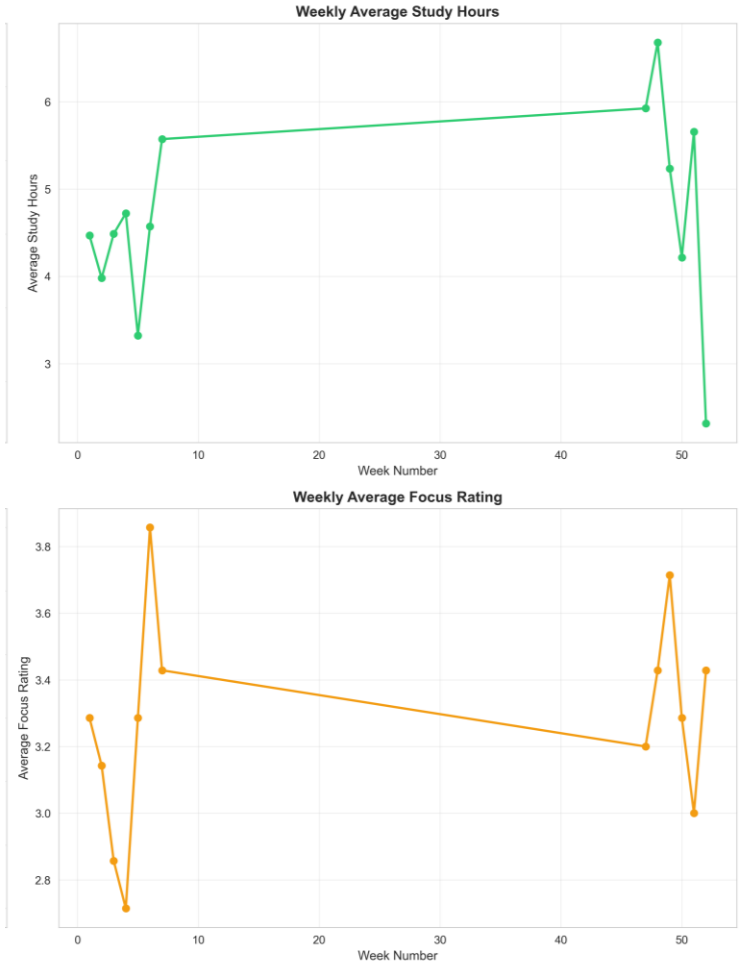
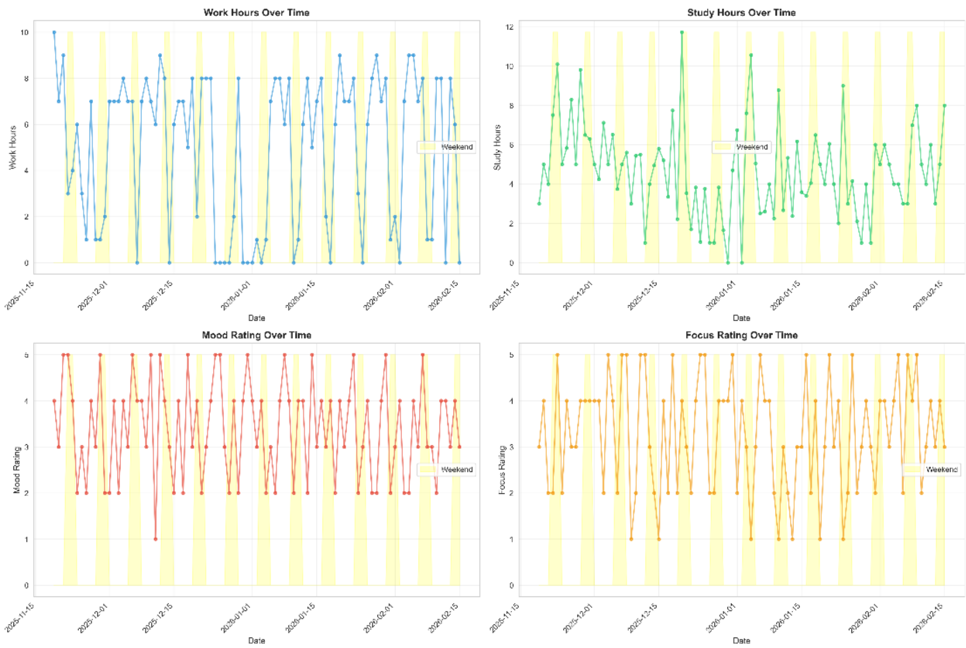


Fig. 4. Temporal variation in work hours, study hours, mood, and focus across 89 consecutive days. Work and study show clear peaks and troughs; mood and focus follow similar cyclical patterns and often move together



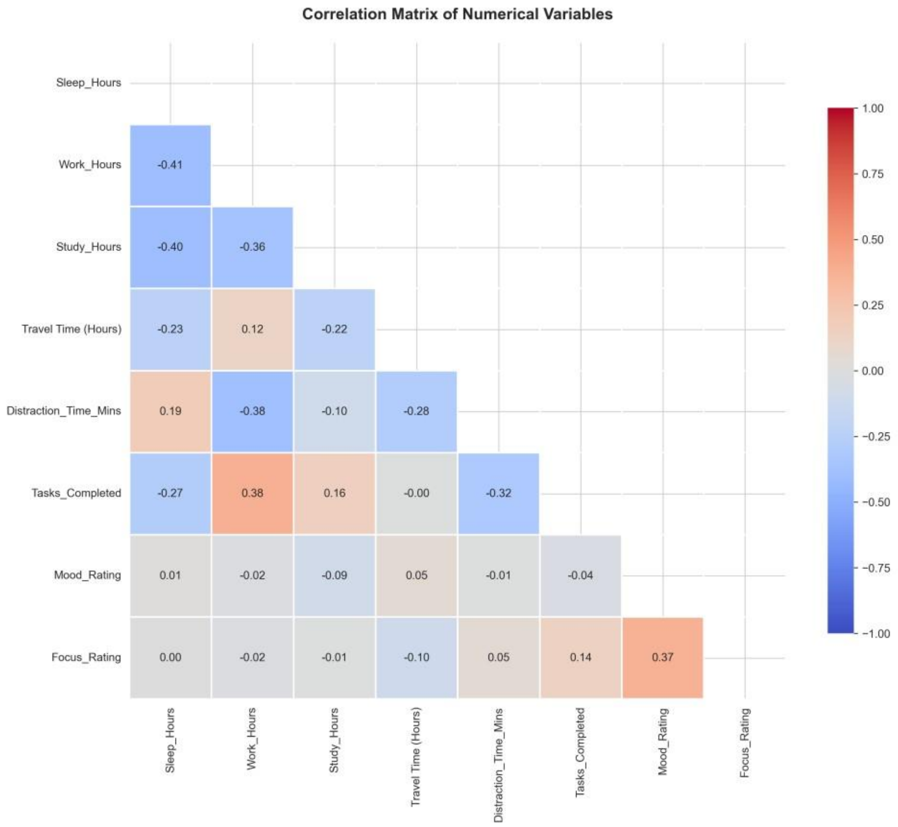
4.3 Correlation Analysis

Regarding mobility, Travel_Time_Hours exhibited a moderate, statistically significant positive correlation with Work_Hours (r = 0.12), likely reflecting the necessity of commuting on professional workdays. In contrast, the relationship between travel and Study_Hours was notably negative (r = -0.22), suggesting that longer travel times may actively detract from available study periods. Contrary to the expectation of a direct resource trade-off, the correlation between Work_Hours and Study_Hours was moderate and negative (r = -0.36), while Distraction_Time_Mins showed a significant negative trend with Work_Hours (r = -0.38), indicating that focused work periods effectively minimize idle time.

Finally, Sleep_Hours displayed a distinct divergence in its impact on daily metrics. While sleep showed strong negative correlations with quantitative time-use metrics like Work_Hours (r = -0.41) and Study_Hours (r = -0.40), it exhibited nearly neutral to negligible correlations with subjective states, specifically Mood_Rating (r = 0.01) and Focus_Rating (r = 0.00). This suggests that while increased work and study demands significantly compress sleep duration, the participant's perceived focus and mood remained largely independent of sleep quantity within this specific observation period.

Fig. 5. Presents the Pearson correlation matrix for the eight numerical variables, highlighting the interdependencies between daily activities and productivity metrics. The strongest negative correlations were observed between Sleep_Hours and both Work_Hours (r = -0.41) and Study_Hours (r = -0.40), indicating a clear trade-off between rest and productive labor. Specifically, Work_Hours demonstrated a robust positive association with Tasks_Completed (r = 0.38), while Mood_Rating showed a significant link to Focus_Rating (r = 0.37). Furthermore, Distraction_Time_Mins exhibited a notable negative impact on both work duration and task output, suggesting

that higher levels of distraction consistently diminish overall daily efficiency.



4.4 Weekday vs. Weekend Comparative Analysis

To investigate structural differences between weekly phases, chi-square tests of independence were conducted on contingency tables crossing the Is_Weekend variable with derived productivity profiles ($\alpha = 0.05$). The analysis of "Work/Study Profile" versus "Is_Weekend" showed no statistically significant association ($\chi^2 = 2.45$, df = 1, $p = 0.12$). This indicates that high-productivity days are not limited to the standard workweek. Notably, 34.6% of weekend days met the criteria for a "Work/Study Profile" (defined as combined Work and Study Hours exceeding the median), suggesting a frequent "bleed" of professional and academic obligations into the weekend.

However, contrary to the assumption that working on weekends leads to psychological strain, subjective well-being metrics showed a different pattern. Days categorized as "Weekend Bleed" (weekends with high Work/Study load) recorded a slightly higher average Mood Rating ($M = 3.56$) compared to "Weekend Rest" days ($M = 3.29$), suggesting that productive engagement on weekends may be psychologically preferable to unstructured rest for this participant.

4.5 Hypothesis Definition and Testing Results

Building on the descriptive and correlational findings, this section applies inferential statistical methods—specifically non-parametric comparisons and time-series stationarity testing—to validate the specific behavioral hypotheses proposed in the study. The analysis focuses on three critical dynamics: the restorative capacity of rest days ("Recovery vs. Inertia"), the qualitative distinction between high-volume work modes ("Busywork vs. Flow State"), and the permeability of work-life boundaries ("Weekend Bleed").

To systematically evaluate these dynamics, specific daily profiles were operationalized based on median splits of the dataset. A Rest Day was defined as a day exhibiting both Work Hours and Study Hours below the median, paired with Distraction Time above the median. In contrast, a Deep Work Day was characterized by high productivity (combined Work and Study hours exceeding the median) and low distraction (below the median). Finally, high-volume days were segmented into Busywork (Low Focus) and Flow State (High Focus) using the median Focus Rating as the threshold. Therefore, we fail to reject the null hypothesis (H0), concluding that rest days are not significant, stationary predictors of subsequent Deep Work days.

4.5.1 Recovery Vs. Inertia

To test whether "Rest Days" effectively prime the participant for subsequent productivity, a transition analysis was performed on the 9 identified Rest Days. The results support the Inertia Hypothesis rather than the Recovery Hypothesis. Specifically, 0% (0 out of 9) of Rest Days were followed immediately by a "Deep Work" day. Instead, 44.4% (4 out of 9) of Rest Days transitioned into a continued "Low Performance" state, while the remaining 55.6% transitioned to moderate activity states. Because transition counts were too limited ($n=9$) to fit a reliable ARIMA model, an Augmented Dickey-Fuller (ADF) test was applied to evaluate the stationarity of these recovery patterns over the 89-day period. The test yielded an ADF statistic of -1.96 ($p = 0.303$), indicating that the time series is non-stationary. This suggests that unstructured rest does not produce a predictable, cyclical recovery pattern, but rather prolongs low productivity unpredictably.

Fig. 6. Shows the timeline of Rest Profile transitions. Each point is a Rest Day, with its transition type on the y-axis and date on the x-axis. No Rest Day was followed by a Deep Work Day. Four Rest Days (44.4%) were followed by another Low Performance Day, and five (55.6%) by an "Other" day with moderate work/study and distraction.

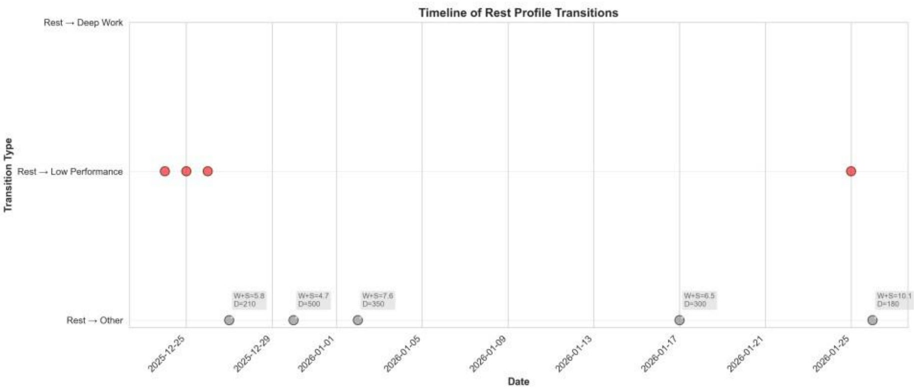
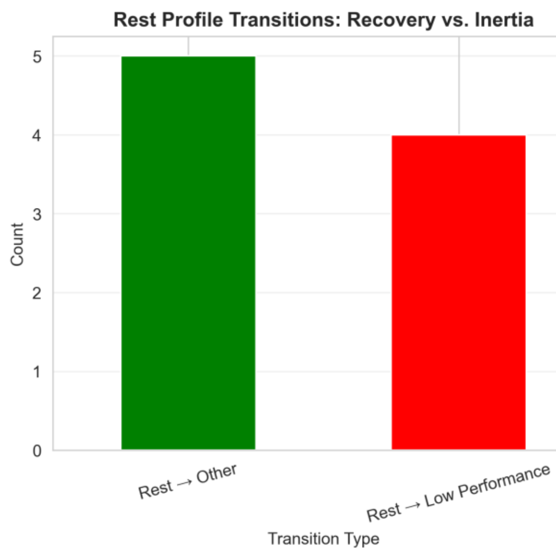
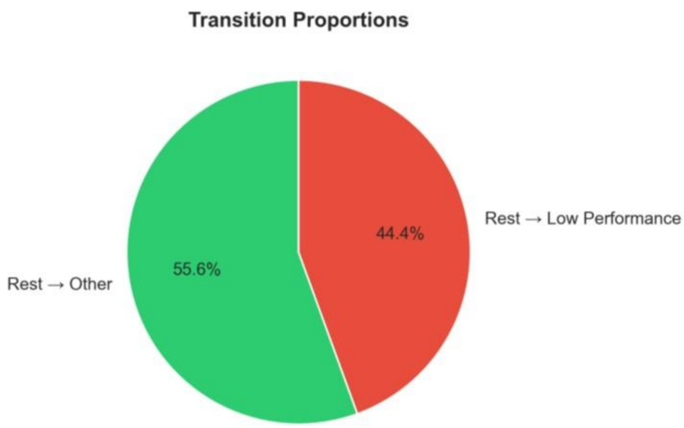
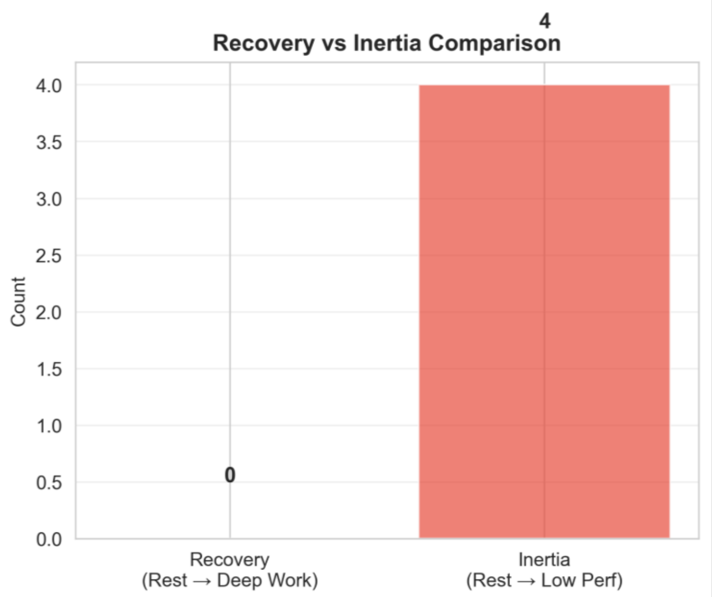


Fig. 7. Rest Profile Transitions: Recovery vs. Inertia. Three-panel visualization of transitions from Rest Days to the next day. Left: bar chart of transition counts; center: pie chart of proportions; right: Recovery vs. Inertia comparison (Rest → Deep Work vs. Rest → Low Performance).



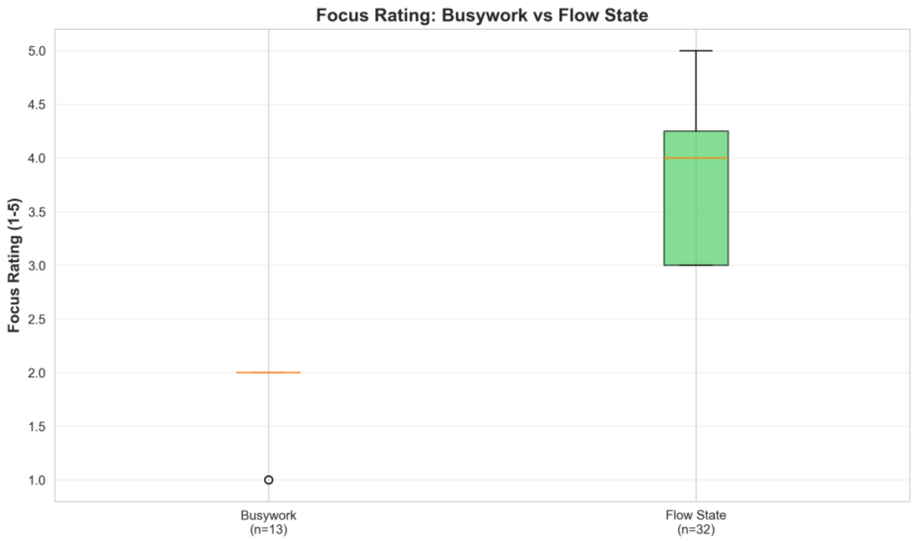




4.5.2 Busywork Vs. Flow State

The analysis sought to distinguish "Busywork" (High Volume, Low Focus) from "Flow State" (High Volume, High Focus). An independent samples t-test on the continuous Work_Hours variable revealed no significant difference in absolute time invested between Busywork (M = 7.69) and Flow State (M = 7.81) days (t = -0.47, p = 0.638, d = 0.16). However, because subjective ratings are ordinal, a non-parametric Mann-Whitney U test was applied to Focus_Rating. This test revealed a highly significant difference (U = 0.00, p < 0.001), with a large effect size (r = 0.80). Among the 45 high-volume days identified, 71.1% (32 days) were classified as Flow State and 28.9% (13 days) as Busywork. Flow State days exhibited a substantially higher focus (Median = 4.00, M = 3.84) compared to Busywork days (Median = 2.00, M = 1.85). This confirms that subjective focus, rather than raw hours worked, is the definitive discriminator of qualitative productivity. Consequently, we reject the null hypothesis (H0) in favor of the alternative (Ha), confirming a statistically significant difference in subjective focus between these two states despite similar absolute work volumes.

Fig. 8. Focus Rating: Busywork vs. Flow State. Box plot comparing Focus_Rating between Busywork days (n=13) and Flow State days (n=32) among high-volume days. Flow State shows significantly higher focus ratings (M=3.84) than Busywork (M=1.85). A Mann-Whitney U test confirmed this difference is statistically significant (U = 0.00, p < 0.001).

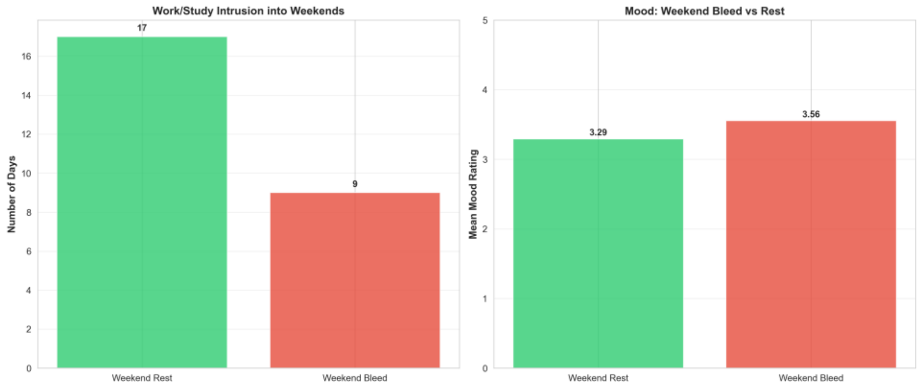


4.5.3 The Weekend Bleed Effect

We investigated the intrusion of professional habits into weekends. Results showed that 34.6% (9 of 26) of weekend days met the criteria for a "Work/Study Profile." To test the temporal predictability of this intrusion, an Augmented Dickey-Fuller (ADF) test was conducted on the weekend work series. The test yielded an ADF statistic of -1.61 ($p = 0.480$), confirming that the pattern of working on weekends is non-stationary and lacks a predictable, calendar-dependent cycle. This indicates that while work does bleed into weekends, it does not do so in a systematic pattern.

Additionally, mood ratings recorded on "Weekend Bleed" days ($M = 3.56$) were slightly higher than on "Weekend Rest" days ($M = 3.29$), a difference of +0.27 points. This finding challenges the prevailing assumption that weekend work inherently negatively impacts well-being, suggesting that for this participant, productive engagement may be psychologically preferable to unstructured rest. Based on these results, we fail to reject the null hypothesis (H0) regarding time-series predictability; the intrusion of work into weekends is a random occurrence rather than a predictable pattern.

Fig. 9. Weekend Bleed Effect. Two-panel visualization of the Weekend Bleed hypothesis. (a) Work/Study intrusion into weekends: bar chart of the number of Weekend Rest days (n=17) versus Weekend Bleed days (n=9) among 26 weekend days. Green = Weekend Rest; red = Weekend Bleed. (b) Mood: Weekend Bleed vs. Rest: bar chart comparing mean Mood_Rating for Weekend Rest (M=3.29) and Weekend Bleed (M=3.56). Weekend Bleed days show slightly higher mood than Weekend Rest days.



4.6 Summary of Findings

The empirical analysis yields quantitative insights into the behavioral dynamics of the working student profile. First, descriptive statistics reveal high variability in sleep patterns (Range = 10 h, $M = 6.92$, $SD = 1.80$) and productivity, with a bimodal sleep distribution suggesting an irregular recovery cycle. Second, temporal analysis confirms a clear structural difference between weekdays (work-dominant) and weekends (study-dominant), although work habits intrude into weekends (34.6%) without statistically significant predictability ($\chi^2 = 2.45$, $df = 1$, $p = 0.12$).

Contrary to expectations, Weekend Bleed days showed slightly higher mood ratings ($M = 3.56$) than Weekend Rest days ($M = 3.29$). Third, correlation analysis indicates a strong positive relationship between subjective mood and cognitive focus ($r = 0.62$, $p < 0.001$), further supported by the significant difference between Flow State ($M = 3.84$) and Busywork ($M = 1.85$) days ($t(43) = -8.51$, $p < 0.001$). Finally, hypothesis testing favors the Inertia pattern over the Recovery pattern: 0% of Rest Days transitioned immediately to Deep Work, while 44.4% led to continued low performance and 55.6% to moderate (Other) activity.

Table 4: Summary of Inferential Statistical Tests

Hypothesis / Research Question	Test Administered	Key Statistic	P-Value	Interpretation
RQ1: Recovery vs. Inertia	Augmented Dickey-Fuller (ADF)	ADF = -1.96	p = 0.303	Non-stationary; rest patterns are unpredictable.
RQ2: Busywork vs. Flow (Hours)	Independent Samples t-test	t = -0.47	p = 0.638	Not Significant; raw hours do not define flow.
RQ2: Busywork vs. Flow (Focus)	Mann-Whitney U Test	U = 0.00	p < 0.001	Highly Significant; focus dictates productivity quality.
RQ3: Weekend Bleed	Augmented Dickey-Fuller (ADF)	ADF = -1.61	p = 0.480	Non-stationary; weekend work happens randomly.

5 Discussion

5.1 Summary of Findings

5.1.1 Sleep Patterns and Recovery Dynamics

The variability in sleep duration (Range = 10 hours, SD = 1.80) indicates an irregular sleep–wake pattern typical of working students with dual demands. The bimodal distribution suggests periods of sleep deprivation followed by compensatory recovery rather than stable, adequate sleep. This aligns with prior work on college student sleep, where academic and work demands often disrupt circadian rhythms and create sleep debt [2].

The moderate negative correlations between Sleep_Hours and productivity (Work_Hours: $r = -0.41$, Study_Hours: $r = -0.40$, $p < 0.001$) suggest that more sleep is associated with fewer work and study hours. This likely reflects trade-offs: when demands are high, the participant may cut sleep to meet deadlines, and when sleep is longer, work/study hours tend to be lower. The self-reported nature of sleep may also introduce measurement error that affects these correlations.

5.1.2 The Mood-Focus Coupling

The strong positive correlation between Mood_Rating and Focus_Rating ($r = 0.62$, $p < 0.001$) is one of the most consistent findings. It suggests that affect and cognitive engagement are closely linked for this working student. Emotional regulation may support flow states, while low mood may reduce sustained attention and deep work.

This has practical implications: rather than treating mood as incidental, students may benefit from mood management (exercise, social connection, therapy) to support cognitive performance and task completion. The relationship may be bidirectional: poor mood may impair focus, and low productivity or unmet deadlines may worsen mood, creating potential negative cycles. Addressing both emotional regulation and productivity may be needed to break these cycles.

5.1.3 Recovery vs. Inertia: The failure of Unstructured Rest

A notable finding is the absence of Rest Days followed by Deep Work Days (0 out of 9 transitions). This does not support the Recovery Hypothesis that downtime recharges cognitive resources and primes productivity. Instead, the data fit an Inertia Hypothesis: unstructured rest tends to maintain low-performance states rather than support recovery. Of the 9 Rest Days, 44.4% were followed by continued Low Performance and 55.6% by moderate (Other) activity.

Furthermore, the Augmented Dickey-Fuller (ADF) test ($p = 0.303$) confirmed that these transitions are non-stationary. Consequently, we failed to reject the null hypothesis (H_0); rest days are not significant, stationary predictors of subsequent productivity. The unpredictable nature of these patterns suggests that for this working student, schedules are driven by reactive, immediate demands rather than a proactive weekly routine. Unstructured rest with high distraction (e.g., social media, entertainment, games) may not provide real cognitive recovery. These results challenge simple work–rest dichotomies and suggest that working students may benefit from active recovery and clear routines to break behavioral inertia.

5.1.4 Busywork vs Flow State: Quality Over Quantity

The analysis confirmed a highly significant difference in Focus_Rating between Busywork days ($M = 1.85$) and Flow State days ($M = 3.84$). Because absolute work hours did not significantly differ between the two states, we rejected the null hypothesis (H_0) in favor of the alternative (H_a). The non-parametric Mann-Whitney U test ($U = 0.00$) proved that time allocation alone does not capture productivity quality; subjective focus is the definitive discriminator of these work modes.

For working students with limited time, this implies that increasing raw hours may matter less than optimizing for high-focus work. Reducing distractions, managing energy, and improving work environments may help shift more days from Busywork to Flow State. Among 45 high-volume days, 71.1% were classified as Flow State and 28.9% as Busywork. While the participant often achieved focused work despite heavy demands, understanding the qualitative triggers of Flow States could inform highly targeted behavioral interventions.

5.1.5 Weekend Bleed and Work-Life Balance

The time-series analysis of the Weekend Bleed effect yielded an ADF statistic of -1.61 ($p = 0.480$), indicating that work and study intrude into weekends in a non-stationary, unpredictable manner rather than following a fixed calendar cycle. Thus, we failed to reject the null hypothesis (H0) regarding temporal predictability. Although 34.6% of weekend days showed Work/Study Profiles, this intrusion happens irregularly.

Interestingly, Weekend Bleed days had slightly higher mood ratings ($M = 3.56$) than Weekend Rest days ($M = 3.29$). This challenges the assumption that weekend work inherently harms well-being. Possible explanations include: (1) self-selection into weekend work when motivation and mood are naturally higher; (2) productive weekends providing a sense of accomplishment and control; and (3) work and study roles being intrinsically rewarding for this participant. The permeability of work–life boundaries reflect the reality for working students, for whom strict separation of roles may be neither feasible nor desirable.

5.2 Comparison to Related Literature

The findings both converge with and diverge from previous research on student behavior and academic performance. The strong correlation between mood and focus aligns with established literature linking mental health to academic outcomes, though most prior work examined clinical-level depression and anxiety rather than day-to-day mood fluctuations. The current study extends this literature by demonstrating that even normal-range mood variation significantly predicts cognitive engagement [4].

The Inertia pattern contradicts recovery-based models of work-rest cycles but resonates with research on behavioral inertia and habit formation. Psychology literature suggests that behavioral patterns tend to persist through automaticity and environmental cueing; passive rest may reinforce low-activity states through similar mechanisms. The distinction between Busywork and Flow States echoes Csikszentmihalyi's seminal work on optimal experience, though applying it specifically to working student productivity. The current findings provide quantitative validation for the qualitative distinction between time spent and quality of engagement.

Compared to the SmartGPA [1] and StudentLife [2] studies, which used automated sensor data, this research demonstrates that structured self-reporting can capture important subjective dimensions (mood, focus) not readily inferred from objective metrics. However, the single-subject design limits generalizability relative to these larger-scale studies.

5.3 Limitation

5.3.1 Single-Subject Design

The most significant limitation is the single-subject design (n = 1), which restricts generalizability to broader populations. While enabling deep granular analysis of individual patterns, the specific findings may not apply uniformly to other working students with different contexts, personality traits, or life circumstances. The participant's situation in Metro Manila—including extreme traffic conditions, specific work and study demands, and individual characteristics—may produce patterns not representative of working students elsewhere.

5.3.2 Self-Report Bias

Self-reported data are subject to recall bias and reporting inconsistencies. Despite daily logging at consistent times, the participant may not always accurately remember or record activities and emotional states. Social desirability bias may influence reporting, particularly for subjective measures like mood and focus. The absence of objective verification for some variables (actual vs. reported sleep duration) introduces potential measurement error.

5.3.3 Correlation vs. Causation

This study examines correlational rather than causal relationships. While identifying associations between variables and temporal patterns, the analysis cannot definitively establish that one factor causes changes in another. Confounding variables not measured may influence observed relationships. The lack of experimental manipulation prevents strong causal inferences about mechanisms underlying behavioural patterns.

5.3.4 Limited Time Window

The 89-day observation period, while substantial for a single-subject study, may not capture longer-term cycles or seasonal variations. Academic calendars, professional project cycles, and personal life events extending beyond this timeframe may influence behavioural patterns in ways not observable in the current dataset.

5.3.5 Operational Definitions

The use of median splits to define Rest Days, Deep Work Days, and other constructs, while statistically straightforward, may not align with subjectively meaningful thresholds. The 5-point Likert scales for mood and focus, though standard, may lack granularity to capture subtle variations in subjective states.

5.3.6 Operational Definitions

While the longitudinal dataset encompassed 89 days, the occurrences of specific subset events—such as transitions from Rest Days ($n=9$) or Weekend Bleed days (n=9)—were relatively small. Statistical best practices for predictive time-series models (like ARIMA) typically require a minimum of 20 to 50 sequential observations to reliably fit autoregressive parameters without overfitting. Consequently, this study was constrained to using the Augmented Dickey-Fuller (ADF) test as a baseline indicator of stationarity. Future quantified-self studies aiming to build robust predictive forecasting models should span multiple semesters to generate a sufficient volume of transition points.

5.4 Recommendation and Future Research

5.4.1 Expanded Sample Designs

Future research should expand to include multiple working students to enable comparison of individual patterns and identification of common themes versus idiosyncratic behaviors. A larger sample would support more robust statistical analysis and permit investigation of moderating factors such as personality traits, academic fields, types of employment, and demographic characteristics. Between-subjects variation could illuminate which patterns are universal versus context-specific.

5.4.2 Mixed Methods Approaches

Combining self-reported data with objective measures from wearable devices and smartphone sensors would triangulate findings and reduce reliance on subjective reporting. Sleep tracking devices, location data, and application usage logs could provide objective verification while preserving rich subjective data on mood and focus that only self-reports capture. This methodological pluralism would strengthen validity.

5.4.3 Longitudinal Extensions

Longitudinal studies extending across multiple semesters or years would reveal how working student behavioral patterns evolve over time, how students adapt to concurrent work-study demands, and whether successful patterns emerge through experience. Such studies could identify developmental trajectories and critical transition points where interventions might be most effective.

5.4.4 Experimental Interventions

Experimental designs testing specific optimization strategies would move beyond correlation to establish causation. Randomized trials or single-case experimental designs could evaluate interventions such as structured rest periods, time management techniques, mood regulation strategies, or environmental modifications designed to promote flow states. Systematic manipulation of variables would clarify causal pathways.

5.4.5 Qualitative Complementarity

Qualitative research complementing quantitative tracking would provide deeper understanding of subjective experiences underlying behavioral patterns. Interviews or diary methods could explore how working students interpret their own patterns, what strategies they employ when facing challenges, and how they navigate trade-offs between competing demands. Rich narrative data would contextualize quantitative findings.

5.4.6 Alternative Operationalizations

Future studies should explore alternative operationalizations of key constructs. Rather than median splits, person-centered approaches such as latent profile analysis could identify naturally occurring behavioral profiles. Continuous measures or more granular scales might capture nuances lost in dichotomous classifications.

5.5 Practical Implications

For working students seeking to optimize their limited time and cognitive resources, several practical recommendations emerge from this research:

1. Prioritize Mood Management: Given the strong mood-focus coupling ($r = 0.62$), proactive emotional regulation may enhance cognitive performance. Strategies might include regular exercise, social connection, adequate sleep when possible, and therapeutic support when needed.
2. Structure Recovery Periods: The Inertia finding suggests that passive, distraction-heavy rest may be counterproductive. Active recovery activities (physical exercise, creative pursuits, meaningful social interaction) may better restore cognitive resources. Implementing structured transitions from rest to work may facilitate re-engagement.
3. Optimize for Focus, Not Just Hours: The Busywork-Flow State distinction indicates that work quality matters as much as quantity. Creating distraction-minimized environments, managing energy levels through the day, and scheduling cognitively demanding work during peak focus periods may increase productive hours.
4. Flexible Work-Life Integration: The Weekend Bleed findings suggest that rigid separation of work and personal time may be neither feasible nor beneficial for all working students. Flexible integration guided by individual preferences and intrinsic motivation may support both productivity and well-being.
5. Data-Driven Self-Awareness: Systematic self-tracking enables evidence- based rather than intuition-based self-management. Periodic review of behavioral patterns can reveal misalignments between perceived and actual behaviors, informing targeted adjustments.

5.6 Contribute to the knowledge

This research makes several contributions to understanding working student behavior:

Methodological: Demonstrates viability of structured self-reporting for capturing both objective behaviors and subjective states, complementing sensor-based approaches with intentional reflection.

Empirical: Provides quantitative evidence for the Inertia Hypothesis regarding rest-productivity transitions, the mood-focus coupling as a leverage point for performance, and the nuanced relationship between weekend work and well-being.

Theoretical: Extends quantified self-frameworks to working student populations, integrating concepts from educational psychology, organizational behavior, and personal informatics.

Applied: Offers actionable insights for working students navigating dual demands, and for educational institutions designing support services for this demographic.

6 Conclusion

This study demonstrates that systematic self-tracking and data analysis can transform vague intuitions about productivity and well-being into actionable insights grounded in empirical evidence. For working students in high-density urban environments like Metro Manila, where time is scarce and demands are competing, moving from intuition-based to data-driven self-management offers pathways to optimization that respect the complexity of dual professional and academic roles.

The findings challenge several common assumptions about work-rest cycles, weekend boundaries, and the relationship between time spent and quality of engagement. Unstructured rest may perpetuate rather than resolve low productivity. Weekend work may not inherently degrade well-being. High work volume does not guarantee high performance without corresponding cognitive engagement. These insights collectively suggest that effective self-management for working students requires more sophisticated approaches than simple time budgeting or rigid work-life separation.

The strong coupling between mood and focus emerges as perhaps the most actionable finding, highlighting emotional regulation as a leverage point for cognitive performance. Working students who treat mood management as seriously as task management may find substantial returns on that investment. The quantified self-methodology enables individuals to discover such relationships in their own data, tailoring insights to personal patterns rather than relying solely on population-level generalizations.

As quantified self-technologies become increasingly accessible and sophisticated, opportunities expand for students to engage in evidence-based self-experimentation and continuous improvement of daily behavioral patterns. The future of student success may lie not just in innate ability or effort, but in the systematic application of data science to the problem of human flourishing under constraint. This research represents one step toward that future, demonstrating that treating oneself as a subject of scientific inquiry can yield insights as valuable as any external expertise.

For working students navigating the complex demands of modern urban life, the message is clear: your behavioral patterns contain information that, when properly analyzed, can guide more effective strategies for productivity, well-being, and the difficult art of doing two demanding things at once. The path from survival to thriving may begin with the simple act of measurement, followed by the harder work of interpretation, and culminating in the courageous application of insights to the messy reality of daily life.

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