Defying the Blues: Why Monday is Statistically My Best Start to the Week

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***Abstract* – The "Monday Blues" is a widely recognized cultural phenomena that is defined by a drop in mood at the beginning of the week. But according to new educational study, university students' emotional patterns can be more influenced by their academic obligations than by the actual day of the week. This study uses a "Quantified Self" technique to examine the validity of the "Monday Blues" concept. An undergraduate student studying computer science gathered hourly mood logs over a two-month period to create a single-subject dataset ($N = 1$). As a "soft start" to the week filled with leisure activities, Monday turned out to be the day with the positive impact ($M = 0.23$), which was contrary to the expectation. On the other hand, Tuesday was found to be the weekly cycle's lowest point ($M = -0.08$). The statistical significance of this drop was validated by an Independent Samples T-Test ($p = 0.0033$). The "Tuesday Slump" is associated with a significant increase in study effort, according to activity analysis, indicating that situational stresses rather than circadian cycles influence students' well-being. These results support the use of "academic pacing" techniques to lessen the mid-week collapse.**

***Index Terms* – Exploratory Data Analysis, Mood Tracking, Personal Informatics, Quantified Self, Statistical Hypothesis Testing, Student Well-being, Temporal Pattern Mining.**

I. Introduction

The ability to monitor and evaluate behavioral data, including sleep, productivity, and mood, has revolutionized how people perceive their own well-being. Although robust weekly cycles, such as the positive mood effects associated with weekends, have long been identified by population-level studies using social media data [1], these generalized trends might not accurately reflect individual experiences. Developing successful self-regulation techniques requires an understanding of the unique factors that influence one's own mood, especially for students juggling demanding academic schedules.

This study focuses on the analysis of a dataset collected by the subject, a Computer Science student, over two months. Testing the "Monday Blues" hypothesis against individual empirical data is the main objective. Due to the shift from the weekend leisure to work structures, Mondays are frequently viewed culturally as the time of greatest negative affect [2]. This assumption is challenged by recent educational research, though; for example, a 2024 study on student emotions found no evidence of a "Blue Monday" effect but rather of a "Frustrating Tuesday" phenomenon brought on by mounting academic demands [3].

A crucial question is brought up by this contradiction: Is the "Monday Blues" a cultural stereotype or a biological reality? Additionally, studies indicate that positive affect and high academic time are inversely connected [4], suggesting that a student's mood may be more influenced by their course schedule than by the day of the week.

Objectives:

1) To quantitatively test the validity of the "Monday Blues" hypothesis by comparing average mood ratings across days of the week.
2) To identify the specific day of the week associated with the lowest mood stability and highest negative affect.
3) To determine the correlation between mood intensity and contextual variables, specifically "Activity Type" (e.g., Studying vs. Entertainment) and "Social Context" (e.g., Alone vs. With Friends).

Research Questions:

1) Does the subject's mood data support the existence of a "Monday Blues" effect, or does it deviate from the common populace?
2) How do specific activities, such as "Studying" versus "Entertainment," influence the variation in Daily Mood Scores?
3) If Monday is not the period of peak negative affect, which day represents the true weekly "slump," and

is this slump driven by academic workload or social isolation?

Hypothesis:

- Alternative Hypothesis (H_a): Monday is statistically different and more affective state than Tuesday.
- Null Hypothesis (H_0): Monday is not statistically different and more affective state than Tuesday.

II. Literature Review

A. *Temporal Patterns of Affect and the Academic Context*

Historical preconceptions regarding weekly mood patterns have been progressively challenged by research into the "Circadian Rhythm of Affect." Recent mental health investigations have refuted the cultural notion of "Blue Monday," which holds that the first day of the week is always the most depressing, as a "pr stunt" with no supporting clinical data [5]. According to empirical research, mood swings are more related to the activity's context than the day itself.

Recent research challenges the conventional "Monday Blues" narrative in the particular setting of student life. There was no evidence of a "Blue Monday" effect in a 2024 study on real-time student emotions. Instead, the researchers discovered a "Frustrating Tuesday" phenomenon, noting that negative emotions like stress and frustration peaked on the second day of the week [3]. This is consistent with more extensive research showing that "academic stress," more especially, the strain of workload and grading. is a strong predictor of poor mental health, frequently surpassing temporal factors [6]. According to these studies, students' negative affect is primarily caused by the accumulation of academic demands rather than the actual day of the week.

B. *Methodological Frameworks: PANAS and POMS*

This study uses standardized psychometric scales, which are still essential to contemporary psychological research, to translate qualitative emotions into quantitative data. A popular tool for measuring various aspects of mood is the Positive and Negative Affect Schedule (PANAS). Although some researchers contend it may not be sensitive to certain physiological stressors, such as sleep deprivation, recent validation studies continue to support its usefulness [7]. In addition, the Profile of Mood States (POMS) [8] enables the evaluation of transient states such as "Tension-Anxiety" and "Fatigue." By employing these well-established metrics, this project guarantees that the individual data gathered is equivalent to more general scientific investigations.

C. *Limitations of Prior Studies and Project Differentiation*

The use of aggregate data, which masks individual variability, is a major drawback of the literature currently in publication. For example, although meta-analyses have found modest but consistent "Monday Blues" effects in general populations, these effects differ greatly when restricted to particular subgroups, such as college students [9]. Moreover, intraday volatility, the abrupt mood changes that take place between a lecture and a leisure activity is frequently overlooked in population-level studies. By using a "Quantified Self" approach, this project sets itself apart. This study directly addresses the gap between generalized stereotypes and individual reality by applying standardized metrics to a high-frequency (hourly) single-subject dataset. This enables a granular examination of how specific contextual factors interact to create a unique weekly mood profile.

III. Methodology

The experimental design utilized to collect and examine longitudinal mood data is described in this section. To find temporal patterns in emotional well-being, the study uses a "Quantified Self" methodology and high-frequency data logging.

A. *Participants*

- This study focuses on tracking the mood of a single subject with high frequency data logging. The subject of this study is a student at the National University.

Table 1: Demographics

Demographics	
Age	22
Program/Course	BS in Computer Science
Specialization	Machine Learning
Year Level	Fourth Year

B. *Data Collection Methods*

Data was collected over two months, from December 1, 2025, to January 31, 2026. The dataset consists of hourly self-reports submitted by the subject during waking hours.

- Variables Collected: Date/Time, Overall Mood Rating, Mood Intensity, Positive Affect (PANAS + POMS "Vigor/Serenity"), Negative Affect (PANAS + POMS "Tension/Depression/Anger/Fatigue"), Who were you with, Where were you, What were you mainly doing.
- Frequency: Data was logged on an hourly basis during waking hours.
- Tools: Data was recorded using Google Forms and Google Sheets and exported as a structured CSV (Comma Separated Values) file for analysis.

C. Operational Definitions

1) *Overall Mood Rating*: A 5-point categorical scale that is used to find out how the subject feels. For statistical analysis, these categories are mapped to integer values:
   - Very Negative (-2)
   - Negative (-1)
   - Neutral (0)
   - Positive (+1)
   - Very Positive (+2)
2) *Mood Intensity*: An ordinal scale (1–5) indicating the strength of the felt emotion (1 = Mild, 5 = Intense).
3) *Positive/Negative Affect*: Specific emotional descriptors from the PANAS and POMS frameworks (e.g., "Vigor," "Tension").
4) *Contextual Variables*:
   - "What were you mainly doing?" (Activity): The primary task being performed (e.g., "Studying," "Entertainment").
   - "Where were you?" (Location): The current whereabouts of the subject.
   - "Who were you with?" (Social Context): The presence of others (e.g., "Family," "Classmates").

D. Data Cleaning

Raw data was processed using Python (Pandas library) to ensure consistency and usability.

- Completeness Check: The dataset was assessed for missing values. Core variables including Overall Mood Rating, Activity, Location, and Social Context contained zero missing values.
- Handling Null Affects: The "Negative Affect" column contained 614 null entries (out of the total dataset). These were not treated as errors but were interpreted as instances where no significant negative emotion was present (i.e., a neutral or positive state). Similarly, the 88 missing entries for "Positive Affect" were treated as baseline states.
- Text Standardization: Categorical labels with inconsistent apostrophes were merged (e.g., "Relative's Home" vs. "Relative's Home") to ensure accurate grouping.

E. Statistical Analysis

Using statistical tools, the processed dataset was examined to identify significant temporal trends.

- Mean mood scores were calculated for each day of the week to establish a baseline and identify the peak and trough of the subject's weekly mood cycle.
- An Independent Samples T-Test was conducted to determine if the difference in mean mood scores between Monday and Tuesday was statistically significant. The significance level was set at $\alpha = 0.05$.
- Bar charts were generated to visually compare the distribution of activities on the highest-rated day against the lowest-rated day.

IV. Results

A. Descriptive Statistics

The dataset consisted of $N = 969$ hourly mood logs collected over 62 days. The Overall Mood Score for the entire duration was slightly positive ($M = 0.13, SD = 0.85$), with a Median of zero ($0 = Neutral$). This indicates that the subject's baseline affective state is predominantly neutral-to-positive, with deviations into negative affect being less frequent than deviations into positive affect.

Table 2: Summary Statistics for Mood Variables

Variable	Mean (M)	Median	Std. Dev (SD)	Min	Max
Mood Score (-2 to +2)	0.13	0.00	0.85	-2.00	2.00
Mood Intensity (1 to 5)	3.11	3.00	1.04	1.00	5.00

B. Distribution of Affect

With the highest frequency of observations centered around "Neutral" (0) and "Positive" (+1), the mood score distribution (*Figure 1*) shows a negative skew. A resilient emotional baseline is further supported by the fact that "Very Negative" (-2) and "Negative" (-1) states make up a small portion of all entries.

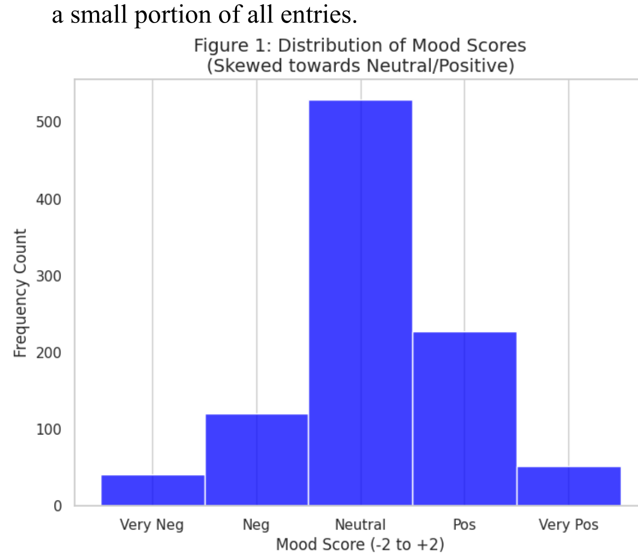

Figure 1: Distribution of Mood Scores

C. Time-Series Trends

Consistent volatility is revealed by a longitudinal analysis of the daily average mood score (*Figure 2*). There are noticeable troughs that correspond to particular dates, even though the trend line primarily oscillates around the neutral baseline ($y = 0$). These declines are consistent with the "Tuesday Slump" that was noted during the hypothesis testing stage, in which weekly stressors that occur frequently (like academic deadlines) cause temporary deviations from the mean.

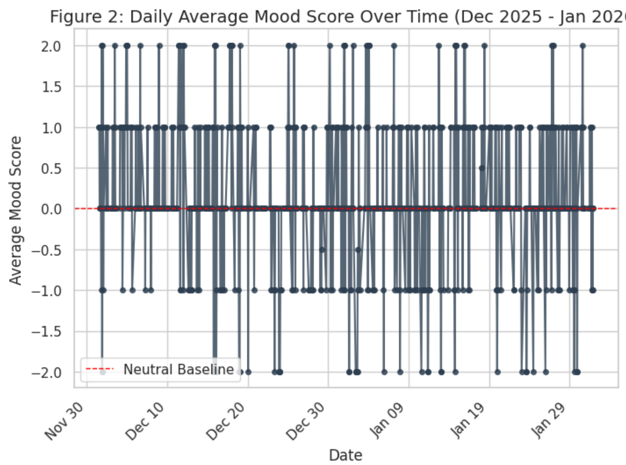

Figure 2: Daily Average Mood Score Over Time

D. Correlation Analysis

A Pearson correlation matrix was computed to examine relationships between Mood Score, Mood Intensity, and Hour of Day (*Figure 3*).

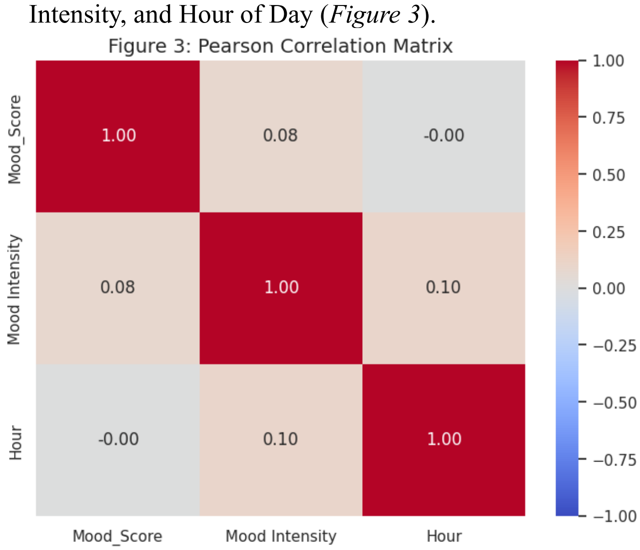

Figure 3: Pearson Correlation Matrix

- Mood Score vs. Mood Intensity ($r = 0.08$): A weak positive correlation was discovered, indicating that an emotion's intensity is unrelated to its valence (i.e., the subject experiences intense calmness just as often as intense stress).
- Mood Score vs. Hour ($r = 0.00$): An absolute zero coefficient pertains that there is absolutely no linear relationship between the time of day and the affective valence of the subject. This implies that situational context (such as the type of activity) is the main determinant of mood fluctuations rather than circadian factors.
- Mood Intensity vs. Hour ($r = 0.10$): A weak positive correlation suggests a slight tendency for emotional intensity to increase as the day progresses, though the relationship is not statistically strong enough to imply a deterministic daily pattern.

E. Hypothesis Testing

An Independent Samples T-Test was used to compare the mean mood scores of Mondays ($M = 0.23$) and Tuesdays ($M = -0.08$) in order to test the "Monday Blues" hypothesis. A statistically significant difference was discovered ($t = 2.97, p = 0.0033$). The null hypothesis (H_0) is rejected with $p < 0.05$, indicating that Monday is statistically different and more affective state than Tuesday (*Figure 4*).

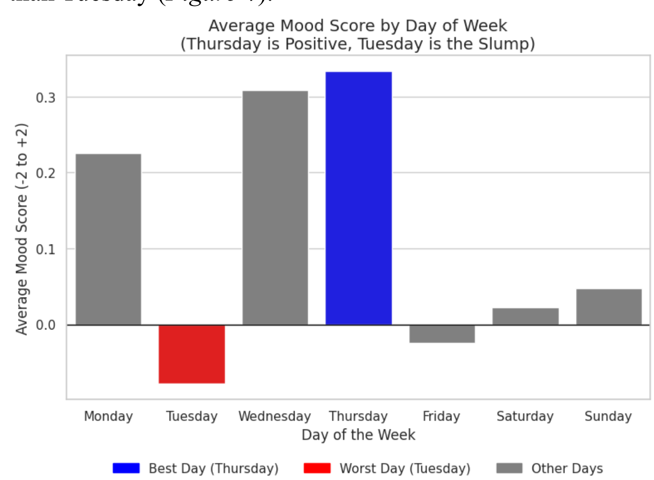

Figure 4: Average Mood Score by Day of Week

V. Discussion

A. Interpretation of Results

This study's main objective was to determine whether the "Monday Blues" hypothesis was true in the particular setting of a computer science student's life. The findings categorically disprove the theory that Monday is the day with the least amount of affect. Rather, after a good start to the week, the data shows a "Tuesday Slump," in which mood sharply drops ($p < 0.05$).

A causal explanation for this change can be found in the frequency analysis of daily activities. The subject uses Monday as a "soft start" to the academic week, as evidenced by the high positive mood ($M = 0.23$) on Monday and the prevalence of "Entertainment" and leisure-based activities. On the other hand, Tuesday's steep drop ($M = -0.08$) corresponds with a change toward "Studying." This suggests that the subject's mood is influenced by the demands of the day's activities rather than the actual calendar day. The correlation analysis, which showed that affective valence is purely situational rather than circadian, further supports this conclusion with a coefficient of $r = 0.00$ between Mood Score and Hour of Day.

B. *Comparison with Prior Studies*

These results contradict with those of broad population-level studies, such those conducted by Golder and Macy [1] and Ellis et al. [2], which found Monday to be the lowest point of the weekly mood cycle. However, those studies primarily analyze the working-age population, where Monday represents the abrupt return to the 9-to-5 workforce.

Most importantly, this study's findings are in line with current studies on schooling. The discovery of a "Tuesday Slump" validates the results of Camerman et al. [3], who noted that students had a "Frustrating Tuesday" impact. According to their research, Tuesday is when the reality of weekly academic deliverables kicks in, whereas Monday is typically seen with anticipation or low-stakes involvement. Additionally, Pascoe et al. [6] claim that academic pressure is the main factor influencing students' well-being, overriding their natural circadian cycles, is supported by the decoupling of mood from time of day.

C. *Limitations*

1) Sample Size ($N = 1$): The findings are particular to the individual's unique schedule and psychology as it is "Quantified Self" research. Without more replication, they cannot be generalized to the broader student body.
2) Self-Report Bias: The use of subjective logging raises the possibility of bias. The "Missing at Random" data patterns seen in the negative affect columns may have resulted from the subject's subconsciously exaggerated mood ratings on Mondays or avoidance of logging entries at times of intense stress.
3) Missing Data: Null values made up a substantial portion of the "Negative Affect" column (614 entries). Although this was interpreted as the lack of negative feeling, it restricts the analysis's granularity with respect to certain negative states, such as weariness or anxiety.

D. *Recommendations and Future Work*

1) For Students: Students should consider "pacing" their academic load. Moving certain academic assignments from Tuesday to Monday might balance out the weekly mood curve and avoid the steep drop shown in this study since Monday serves as a high-mood enhancer.
2) For Future Research: In order to support subjective mood evaluations, future versions of this study should incorporate objective physiological data, such as heart rate variability (HRV) or screen time logs. Furthermore, using "Ecological Momentary Assessment" (EMA) applications that remind users at random times may lessen the possibility of data loss during times of high stress.

VI. Conclusion

The purpose of this study was to use high-frequency data to evaluate the "Monday Blues" theory empirically. The study sought to ascertain if the cultural expectation of a "dreadful Monday" matched the actual experience of a computer science student by examining longitudinal mood logs over a two-month period.

A. *Summary of Findings*

The conventional "Monday Blues" narrative is categorically refuted by the statistics. Monday was the day with the positive impact ($M = 0.23$), which was unexpected because it marked a calm start to the week filled with leisure and low-stress activities. A statistically significant T-test ($p = 0.0033$) confirmed that Tuesday was the genuine dip of the weekly cycle ($M = -0.08$). This demonstrates that there is a "Tuesday Slump," which is caused by a sudden rise in academic workload and study demands rather than circadian cycles.

B. *Personal Insights and Application*

Realizing that mood is situational rather than temporal is the most significant takeaway from this "Quantified Self" experiment. According to the correlation analysis ($r \approx 0$), well-being does not automatically degrade as the day progresses. This implies that rather than being an unavoidable biological truth, the "dread" that is frequently connected to the beginning of the week is a controllable variable.

Ultimately, this study shows the power of personal informatics: by substituting hard data for cultural stereotypes, students can identify hidden behavioral patterns and create a more resilient weekly routine. In practice, these findings support a strategy of "Academic Pacing." To counteract the "Tuesday Slump," the subject can proactively redistribute a portion of the Tuesday workload to Monday, turning the "soft start" into a more balanced "active start."

References

[1] Golder, S. A., & Macy, M. W. (2011). *Diurnal and Seasonal Mood Vary with Work, Sleep, and Daylength Across Diverse Cultures*. Science. https://doi.org/10.1126/science.1202775

[2] Ellis, D. A., Wiseman, R., & Jenkins, R. (2015). *Mental Representations of Weekdays*. PLOS ONE, 10(8), e0134555. https://doi.org/10.1371/journal.pone.0134555

[3] Camerman, E., Kuppens, P., Lavrijsen, J., & Verschueren, K. (2024). *Real-time fluctuations in student emotions and relations with day of the week, time of the day, and teaching methods*. Frontiers in Education, 9, 1470565. https://doi.org/10.3389/feduc.2024.1470565

[4] Greene, K. M., & Maggs, J. L. (2017). *Academic time during college: Associations with mood, tiredness, and binge drinking across days and semesters*. Journal of Adolescence, 56(1), 24-33. https://doi.org/10.1016/j.adolescence.2016.12.001

[5] Owen, M. (2023). *Busting the Blue Monday myth*. National Centre for Mental Health. https://www.ncmh.info/2022/01/17/busting-the-blue-monday-myth/

[6] Pascoe, M. C., Hetrick, S. E., & Parker, A. G. (2019). *The impact of stress on students in secondary school and higher education*. International Journal of Adolescence and Youth, 25(1), 104–112. https://doi.org/10.1080/02673843.2019.1596823

[7] Dow, C., Wilson, S., McMahon, W. R., Manousakis, J. E., Beatty, C. J., Ogeil, R. P., & Anderson, C. (2025). *Development and preliminary validation of a novel tool to measure Negative and Positive Affect for Sleep (NAP-AS)*. Behavioral Sleep Medicine, 23(5), 633–647. https://doi.org/10.1080/15402002.2025.2508768

[8] McNair, D. M., Lorr, M., & Droppleman, L. F. (1971). *Manual for the Profile of Mood States*. San Diego: Educational and Industrial Testing Service.

[9] Areni, C. S., Burger, M., & Zlatevska, N. (2011). Factors Affecting the Extent of Monday Blues: Evidence from a Meta-Analysis. Psychological Reports. https://doi.org/10.2466/13.20.PR0.109.6.723-733