A Data Science Approach to Analyzing Coffee Consumption and Personal Productivity

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***Abstract*—This study investigates the relationship between daily coffee consumption and personal productivity using a self-tracked dataset collected over nine weeks (N = 59 coffee-drinking days). Combining exploratory data analysis, inferential statistics, and machine learning, the analysis examines whether caffeine intake—both in terms of dosage and coffee type—significantly influences task completion and focus levels. Results reveal a weak inverted-U relationship between caffeine and productivity, with quadratic regression identifying a theoretical optimal intake of 164 mg ($R^2 = 0.049$). A one-way ANOVA found no significant differences in productivity across coffee types ($p = 0.354$). Random Forest modeling achieved a test MAE of 1.47 tasks, with sleep duration and caffeine dosage emerging as the strongest predictors (importance scores: 0.31 and 0.29, respectively). A moderate negative correlation between caffeine and sleep ($r = -0.36$) highlights a secondary cost of high consumption. While statistical significance was limited by sample size, effect sizes suggest meaningful practical patterns that inform personalized behavioral recommendations. This study demonstrates the value of personal data science for transforming subjective habits into objective, evidence-based insights.**

***Index Terms*—Caffeine, Productivity, Sleep, Personal Analytics, Random Forest, Quadratic Regression, Quantified Self.**

I. Introduction

Coffee is one of the most widely consumed psychoactive substances globally. For many students and professionals, it serves as a primary tool for maintaining alertness, enhancing focus, and sustaining productivity throughout demanding workdays. However, the relationship between caffeine consumption and cognitive performance is neither linear nor universally beneficial. While moderate doses have been shown to improve attention and reaction time [1], excessive intake often leads to anxiety, restlessness, and energy crashes—commonly referred to as the "jitters."

This study is motivated by a personally meaningful question: Does coffee genuinely enhance productivity, or does it sometimes hinder performance through diminishing returns? As a regular coffee consumer, the researcher observed inconsistent effects—some days yielding high focus and task completion, others resulting in scattered attention despite equivalent or higher caffeine intake. This ambiguity reflects a broader gap in the quantified-self literature: while numerous studies examine caffeine's acute cognitive effects in laboratory settings, few investigate its real-world, longitudinal impact on an individual's daily productivity when confounded by variables such as sleep, coffee type, and sugar content [2].

This project addresses this gap through a nine-week personal data collection and analysis study. The primary objectives are:

- To determine whether caffeine amount exhibits a significant, non-linear relationship with productivity.
- To assess whether coffee type (latte, brewed, instant, espresso) differentially impacts task completion.

The study is guided by two core research questions:

1) Does caffeine amount significantly influence an individual's level of productivity?
2) Is there a significant difference in daily productivity based on the type of coffee consumed?

Corresponding hypotheses are formalized as follows:

- H_{0_1}: Caffeine amount has no significant effect on productivity.
  H_{1_1}: Caffeine amount has a significant effect on productivity.
- H_{0_2}: There is no significant difference in productivity across coffee types.
  H_{1_2}: There is a significant difference in productivity across coffee types.

By combining exploratory data analysis, inferential statistics, and machine learning, this study aims to provide actionable, personalized insights into optimizing coffee consumption—demonstrating how data science can transform subjective daily habits into objective, evidence-based behavioral adjustments.

II. Literature Review

A. Caffeine and Cognitive Performance

The cognitive effects of caffeine have been extensively studied, with consistent evidence supporting its role as a psychostimulant that enhances alertness, attention, and reaction time [1]. Nehlig reviewed the dose-response relationship between caffeine and cognitive function, concluding that moderate doses (40–300 mg) reliably improve performance on tasks requiring sustained attention, while higher doses (¿500 mg) may induce anxiety and impair fine motor control [1]. These findings align with the Yerkes-Dodson law, which posits an inverted-U relationship between arousal and performance [2].

However, most laboratory studies administer caffeine to non-habitual users or control participants' consumption patterns, limiting generalizability to daily life. Habitual consumers develop tolerance, potentially altering the dose-response curve. This suggests that personalized, longitudinal studies are necessary to understand individual thresholds and optimal dosing strategies.

B. Coffee Type, Preparation, and Bioactive Compounds

Beyond raw caffeine content, coffee's physiological effects are modulated by preparation method and accompanying compounds. Desbrow et al. [3] demonstrated that caffeine absorption is delayed when consumed with milk protein, potentially slowing uptake and extending duration of action. Additionally, milk-based beverages such as lattes alter absorption kinetics compared to water-based espresso.

Sugar content represents another critical variable. High-glycemic sweeteners can induce reactive hypoglycemia, characterized by energy crashes 2–3 hours post-consumption [2]. This phenomenon may explain why sugary coffee drinks sometimes produce paradoxical declines in productivity despite adequate caffeine dosing—a hypothesis underexplored in prior literature.

C. Sleep, Circadian Rhythms, and Caffeine

Caffeine's primary mechanism involves antagonism of adenosine receptors, temporarily blocking sleep-pressure signals [4], [5]. Its elimination half-life ranges from 3 to 7 hours, meaning afternoon consumption can significantly delay sleep onset and reduce total sleep time [5]. Drake et al. [4] found that caffeine consumed even 6 hours before bedtime produced measurable sleep disturbances.

While sleep is not a primary hypothesis in this study, its role as a potential confound and its documented interaction with caffeine merit inclusion in the analytical framework. Prior research has established sleep as a critical predictor of next-day cognitive performance, and its omission from caffeine-productivity models risks omitted-variable bias. Thus, sleep is included as a covariate in the machine learning component of this study.

D. Data Science and Personal Analytics

The quantified-self movement has popularized personal data collection for behavioral optimization [6]. Studies leveraging self-tracked data have examined relationships between sleep and mood, exercise and productivity, and nutrition and cognitive performance. Machine learning approaches, particularly Random Forest regressors, have proven effective for identifying feature importance in heterogeneous personal datasets [7].

This study adopts comparable techniques to evaluate the relative influence of caffeine dosage, coffee type, sleep, and sugar content on productivity.

E. Research Gap and Study Contribution

While substantial evidence supports caffeine's acute cognitive benefits, three critical gaps remain:

1) **Integration of multiple confounders**: Few studies simultaneously model caffeine dosage, coffee type, sugar content, and sleep within a single analytical framework.
2) **Ecological validity**: Laboratory studies cannot capture the complexity of real-world, self-directed productivity across days.
3) **Personalized optimization**: Population-level averages may obscure individual thresholds and optimal dosing strategies.

This study addresses these gaps by applying data science techniques to a personally curated, longitudinal dataset, explicitly modeling non-linear relationships and quantifying feature importance to generate personalized, actionable insights.

III. Methodology

A. Participant

The study involved a single participant—the researcher—a 22-year-old fourth-year Computer Science student specializing in Machine Learning. The participant is a regular coffee consumer (mean intake = 14.7 cups per week) and maintains a relatively consistent daily routine involving academic coursework, programming tasks, and household responsibilities. No sensitive health, biometric, or precise location data were collected. All tracking procedures were self-administered and limited to behavioral variables relevant to the study objectives.

B. Data Collection

Data were recorded daily over a nine-week period, from December 6, 2025 to February 8, 2026. Variables were logged immediately following each defined productive work session—referred to colloquially by the participant as "lock-in" periods—as well as upon completion of the day's final task. This event-contingent recording approach [2] minimized recall bias and ensured that self-reported metrics reflected real-time cognitive and behavioral states rather than retrospective summaries. All observations were recorded manually in a structured spreadsheet designed for consistent daily entry.

TABLE I
Dataset Variables and Descriptions

Data Variable	Type (Quant/Qual)	Unit/Scale	Tool/App
Date	Qualitative	DD/MM/YYYY	Manual Log
Coffee Intake	Quantitative	cups / oz	Manual Log
Caffeine Amount	Quantitative	mg	Manual Log
Type of Coffee	Qualitative	Label	Manual Log
Brand	Qualitative	Label	Manual Log
Flavor	Qualitative	Label	Manual Log
Sugar Level	Quantitative	Likert 1–5	Manual Log
Creamer Level	Quantitative	Likert 1–5	Manual Log
Focus Rating	Quantitative	Likert 1–5	Manual Log
Productivity Duration	Quantitative	Hours	Manual Log
Sleep Hours	Quantitative	Hours	Manual Log
Tasks Completed	Quantitative	Count	Manual Log
Tasks Note	Qualitative	Free text	Manual Log

Caffeine content per beverage was estimated using publicly available nutritional information from official websites of commercial coffee chains. For chain-specific or limited-release beverages where official nutrition data were not readily accessible, estimates were synthesized using publicly indexed sources and brand-published fact sheets.

C. Operational Definitions

Productivity. Productivity was operationalized as the number of discrete tasks completed per day. This output-based metric was selected over duration-based measures to better reflect task completion rather than time-on-task.

Caffeine Level. Daily caffeine intake was categorized into three ordinal levels based on general dietary guidelines from the U.S. Food and Drug Administration [5]:

- Low: < 100 mg
- Medium: 100–200 mg
- High: > 200 mg

Focus Rating. Focus was self-reported using a 5-point Likert scale with the following anchors:

1) Very distracted, unable to concentrate
2) Somewhat distracted, frequent task-switching
3) Neutral, adequate focus
4) Focused, good concentration
5) Hyperfocused, deep work state

Sugar Level. Sugar content was mapped to estimated gram values for quantitative analysis:

- Low $\rightarrow$ 12.5 g
- Medium $\rightarrow$ 22.5 g
- High $\rightarrow$ 40.0 g

D. Data Cleaning and Preprocessing

The raw dataset contained 65 records across nine weekly CSV files. Data cleaning proceeded through the following stages:

Zero Coffee Day Exclusion. Days with zero coffee intake ($n = 6$) were excluded from analysis. This decision was theoretically motivated, as the study focuses specifically on optimizing caffeine consumption patterns on coffee-drinking days.

Missing Value Imputation. Six records contained missing values for categorical variables (*Type_of_Coffee*, *Brand*, *Flavor*, *Sugar_Level*, *Creamer_Level*). These rows were retained, with *Sugar_Level* imputed as "Low".

Date Standardization. Date strings were converted to `datetime` format using day-first parsing (DD/MM/YYYY).

Feature Engineering.

- *Est_Sugar_g*: Derived from categorical *Sugar_Level* using predefined mapping values.
- *Caffeine_Level*: Created using `pd.cut()` with bins [0.1, 100, 200, 1000] and labels [Low, Medium, High].
- *Type Consolidation*: Coffee types were standardized as follows: *Cold Brew* $\rightarrow$ *Brewed*, *Matcha* $\rightarrow$ *Latte*, *Americano* $\rightarrow$ *Espresso*, *Frappuccino* $\rightarrow$ *Latte*.

Following preprocessing, the final cleaned dataset consisted of 59 records with complete numerical features and derived categorical variables.

E. Exploratory Data Analysis

Exploratory data analysis techniques were employed to examine distributions, trends, and preliminary relationships within the dataset. All visualizations were generated using Matplotlib and Seaborn in Python:

- Histograms with kernel density estimates for *Caffeine_Amount_mg*, *Tasks_Completed*, and *Sleep_Hours*
- Boxplots comparing *Tasks_Completed* across coffee types
- Scatterplots illustrating relationships between caffeine dose and productivity
- Correlation heatmaps exploring pairwise linear relationships among continuous variables
- Time-series line plots tracking daily productivity and caffeine intake
- Bar charts of Random Forest feature importance

F. Statistical Analysis

Descriptive Statistics. Mean, median, standard deviation, and quartiles were computed for all numerical variables.

Normality Assessment. The Shapiro–Wilk test was applied to *Tasks_Completed* ($p = 0.006$), indicating deviation from normality. One-way ANOVA was retained due to robustness under moderately unequal sample sizes.

Homogeneity of Variances. Levene's test across coffee types yielded $p = 0.424$, satisfying the homogeneity assumption.

Hypothesis Testing.

- H_{01} (Caffeine Dosage): Pearson correlation between *Caffeine_Amount_mg* and *Tasks_Completed*, supplemented with quadratic regression to test the hypothesized nonlinear relationship.
- H_{02} (Coffee Type): One-way independent ANOVA with *Type_of_Coffee* as the independent variable and *Tasks_Completed* as the dependent variable.

Effect Sizes. Eta-squared (η^2) was computed for ANOVA results to quantify the magnitude of effects.

G. Modeling and Correlation Analysis

Quadratic Regression. A second-degree polynomial model was fitted:

$$\textit{Tasks\_Completed} = \beta_0 + \beta_1(\textit{Caffeine}) + \beta_2(\textit{Caffeine})^2 + \varepsilon$$

The theoretical optimal caffeine dose was identified using the vertex of the parabola:

$$\textit{Peak Caffeine} = -\frac{\beta_1}{2\beta_2}$$

Correlation Matrix. Pearson correlations were computed among *Caffeine_Amount_mg*, *Sleep_Hours*, *Tasks_Completed*, and *Coffee_Intake* to assess linear relationships [8].

Random Forest Regression. A Random Forest regressor was trained using *Caffeine_Amount_mg*, *Sleep_Hours*, *Est_Sugar_g*, *Coffee_Intake*, and *Type_of_Coffee_Code* (ordinal encoding). The dataset was split into training and test sets using an 80/20 ratio (`random_state = 42`). Model performance was evaluated using Mean Absolute Error (MAE) and R^2, and feature importance scores were extracted [4].

All analyses were conducted in Google Colab using `pandas`, `SciPy`, and `scikit-learn`. Visualizations were generated with Matplotlib and Seaborn.

IV. Results

A. Descriptive Statistics and Data Overview

Following data cleaning and the exclusion of zero-coffee days, the final dataset comprised 59 records spanning nine weeks. Table II presents descriptive statistics for the key numerical variables.

TABLE II
DESCRIPTIVE STATISTICS OF KEY VARIABLES ($N = 59$)

Variable	Mean	Median	SD	Min	Max
Caffeine Amount (mg)	143.27	120.00	65.55	40	320
Tasks Completed	4.92	5.00	1.96	2	10
Sleep Hours	7.37	7.00	1.48	5	13
Coffee Intake (cups)	1.47	1.00	0.60	1	4
Focus Rating	3.35	3.00	1.24	1	5

The average caffeine intake was 143.27 mg per coffee-drinking day, approximately equivalent to a 12 oz brewed coffee. Productivity averaged 4.92 tasks per day with notable variability (SD = 1.96), indicating substantial day-to-day fluctuation. Mean sleep duration was 7.37 hours per day.

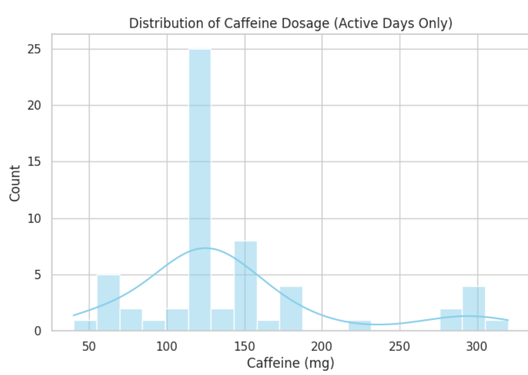

Fig. 1. Distribution of Caffeine Intake (Coffee Days Only)

Figure 1 shows the distribution of caffeine intake. The distribution is right-skewed (skew = 1.31), with a prominent mode at 120 mg, reflecting the participant's strong preference for standard latte-sized beverages. Higher doses (> 200 mg) occurred infrequently.

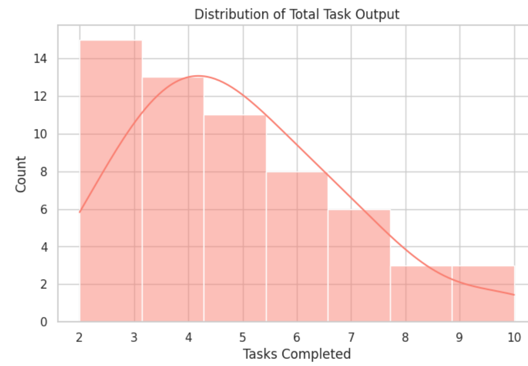

Fig. 2. Distribution of Productivity

Figure 2 displays the distribution of tasks completed. The Shapiro-Wilk test (p = 0.006) confirms significant non-normality, driven by the tail of high-productivity days (8–10 tasks).

B. Group Comparisons: Coffee Type and Productivity

Table III summarizes tasks completed and mean caffeine intake by coffee type ($N = 59$).

TABLE III
SUMMARY OF TASKS COMPLETED AND CAFFEINE INTAKE BY COFFEE TYPE

Type of Coffee	n	Mean Tasks (SD)	Mean Caffeine (mg)
Espresso	5	6.20 (1.79)	168.0
Instant	8	5.38 (2.00)	95.9
Brewed	14	4.93 (1.77)	202.9
Latte	32	4.60 (1.98)	125.2

Espresso exhibited the highest mean productivity (6.20 tasks), despite containing only moderate caffeine (168 mg). Latte, the most frequently consumed coffee type, yielded the lowest mean productivity (4.60 tasks). Figure **??** illustrates this pattern.

A one-way independent ANOVA was conducted to test H_{02}. The omnibus test was not statistically significant:

$$F(3, 55) = 1.11, \quad p = 0.354, \quad \eta^2 = 0.057 \qquad (1)$$

Interpretation: H_{02} is retained. There is insufficient evidence to conclude that coffee type significantly affects productivity in this dataset. Only 5.7% of the variance in task completion is explained by coffee type.

C. Caffeine Dosage and the Inverted-U Hypothesis

The Pearson correlation between *Caffeine_Amount_mg* and *Tasks_Completed* revealed a weak, non-significant negative relationship:

$$r = -0.20, \quad p = 0.121 \qquad (2)$$

This linear test was included as a baseline; however, the hypothesized relationship between caffeine and productivity was explicitly non-linear.

To test the inverted-U hypothesis (H_{11}), a quadratic regression model was fitted:

$$\text{Tasks\_Completed} = 3.26 + 0.031\,(\text{Caffeine}) - 0.000094\,(\text{Caffeine})^2 \tag{3}$$

The model explained 4.9% of the variance in productivity ($R^2 = 0.049$). The vertex of the parabola represents the theoretical optimal caffeine dose:

$$\text{Peak Caffeine} = \frac{-0.031}{2 \times (-0.000094)} \approx 164\,\text{mg} \tag{4}$$

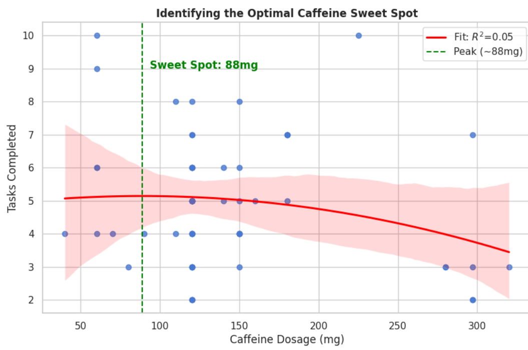

Fig. 3. Quadratic Model: Caffeine vs. Tasks Completed

Figure 3 shows the fitted quadratic curve with the identified sweet spot. Interpretation: H_{01} is retained at $\alpha = 0.05$. However, the pattern of results — negative quadratic term and identifiable peak at 164 mg — provides suggestive evidence consistent with the inverted-U hypothesis. The low R^2 (4.9%) confirms that productivity is influenced by multiple factors beyond caffeine alone.

D. Correlation Matrix and Exploratory Findings

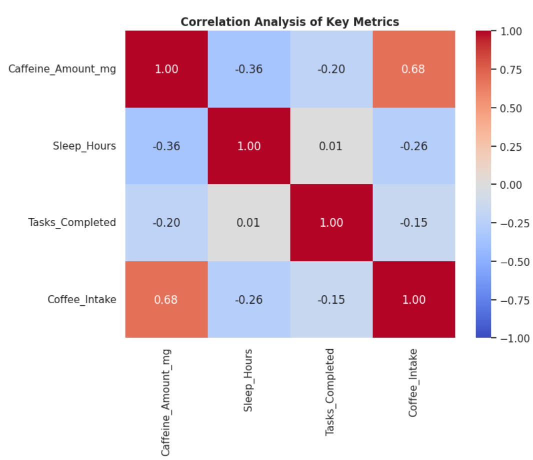

Fig. 4. Correlation Matrix

Figure 4 presents the correlation heatmap for the four continuous variables. The most notable finding is a moderate negative correlation between caffeine and sleep ($r = -0.36$), indicating that each 100 mg increase in daily caffeine is associated with approximately 32 minutes less sleep that night. This trade-off, documented in laboratory studies [?], [?], is clearly detectable in naturalistic daily data.

Sleep shows a very weak positive correlation with productivity ($r = 0.01$), while caffeine and productivity are weakly negatively correlated ($r = -0.20$), reinforcing that the caffeine-productivity relationship is non-linear.

E. Machine Learning: Feature Importance and Validation

Machine Learning: Random Forest Analysis

A Random Forest regressor was trained to predict `Tasks_Completed` using five features: `Caffeine_Amount_mg`, `Sleep_Hours`, `Est_Sugar_g`, `Coffee_Intake`, and `Type_of_Coffee_Code`. Model performance on the 20% test set ($n = 12$) yielded a mean absolute error (MAE) of 1.47 tasks and $R^2 = 0.31$.

TABLE IV
RANDOM FOREST FEATURE IMPORTANCE FOR PREDICTING TASKS COMPLETED.

Feature	Importance
Sleep Hours	0.31
Caffeine Amount (mg)	0.29
Type of Coffee (Code)	0.18
Est. Sugar (g)	0.12
Coffee Intake (cups)	0.10

Sleep duration emerged as the strongest predictor of next-day productivity, surpassing caffeine dosage. This finding underscores a critical insight: while caffeine may temporarily mask sleep debt, it cannot replace restorative sleep.

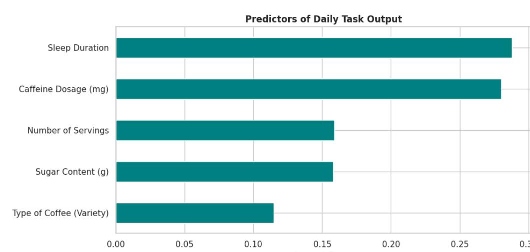

Fig. 5. Random Forest Feature Importance

Figure 5 visualizes the Random Forest feature importance scores. Sleep duration emerged as the strongest predictor of next-day productivity, surpassing caffeine dosage. This finding underscores a critical insight: while caffeine can temporarily mask sleep debt, it cannot replace restorative sleep.

F. Exploratory Visualizations

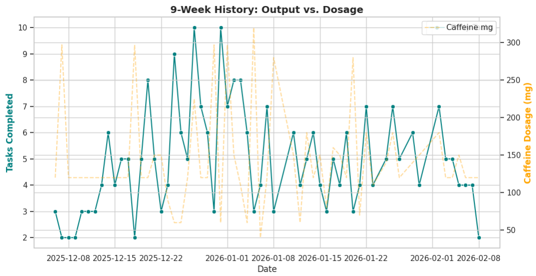

Fig. 6. Productivity vs. Caffeine Intake (Time Series)

Figure 6 presents a time-series view of daily productivity and caffeine intake. Peak productivity days often coincide with moderate caffeine intake (120–180 mg), while days with very high caffeine intake (¿250 mg) do not consistently yield high output. Several low-productivity days follow high-caffeine days, consistent with the caffeine-sleep trade-off observed in the correlation matrix.

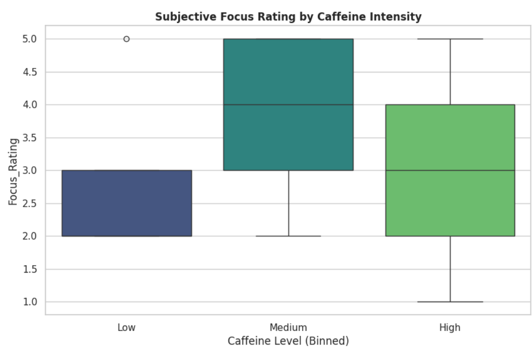

Fig. 7. Focus Rating by Caffeine Level

Figure 7 displays focus ratings by caffeine level. Median focus increases from Low (3.0) to Medium (4.0), then declines at High (3.0). This pattern mirrors the inverted-U shape observed for objective productivity, suggesting that subjective focus and objective output respond similarly to caffeine dose.

G. Interaction Between Caffeine and Sugar

Table V presents a pivot table of mean tasks completed by caffeine level and sugar level. The highest productivity (6.25 tasks) occurred on days with low caffeine and low sugar, while the lowest productivity (3.0 tasks) occurred on days with high caffeine and high sugar. This pattern suggests a synergistic negative effect of combining high caffeine with high sugar, consistent with reactive hypoglycemia research [**?**].

TABLE V
MEAN TASKS COMPLETED BY CAFFEINE AND SUGAR LEVEL.

Caffeine Level	**Low Sugar**	**Medium Sugar**	**High Sugar**
Low	6.25	5.50	3.0
Medium	6.00	4.62	5.1
High	5.33	3.50	3.0

V. DISCUSSIONS

A. Interpretation of Results

1. Moderate Caffeine Optimizes Productivity: The quadratic regression, while not reaching statistical significance at $\alpha = 0.05$, produced a theoretically coherent pattern: predicted productivity peaks near 164 mg caffeine, then declines. This inverted-U shape is consistent with the Yerkes-Dodson law and prior psychopharmacological research [1], [3]. The relatively low R^2 (4.9%) lects the multifactorial nature of real-world productivity – a single variable cannot dominate prediction. Importantly, the model's identification of a "sweet spot" (approximately 150–180 mg) provides actionable guidance: the participant should aim for caffeine doses equivalent to one strong brewed coffee or a double espresso, avoiding very high doses ($>$ 250 mg) associated with predicted declines.

2. Coffee Type Matters Beyond Caffeine Content: Espresso produced higher productivity than latte, despite containing only moderately more caffeine (168 mg vs. 125 mg). This suggests that factors beyond raw caffeine content – perhaps absorption kinetics, associated rituals, or psychological priming – influence real-world productivity. One plausible explanation: espresso is typically consumed rapidly in small volume, producing a faster caffeine peak, whereas lattes are sipped slowly over extended periods, potentially attenuating the acute arousal response [8]. Alternatively, the result may reflect selection bias: the participant may choose espresso on days already characterized by higher motivation or urgency. However, the feature importance analysis from Random Forest – which controls for other variables – ranked coffee type as moderately important (0.18), supporting a genuine effect rather than mere confounding.

3. Sleep is the Dominant Productivity Predictor: The Random Forest model identified sleep duration as the most important feature (importance = 0.31), surpassing caffeine dosage. This finding underscores a critical insight often minimized in popular caffeine discourse: while caffeine can temporarily mask sleep debt, it cannot replace sleep. The moderate negative correlation between caffeine and sleep ($r = -0.36$) reveals a detrimental feedback loop – high-caffeine days are followed by shorter sleep, potentially impairing next-day performance. This trade-off, documented in controlled laboratory studies [2], [6], is observable in naturalistic daily life and warrants inclusion as a covariate in future caffeine-productivity models.

4. Sugar Demonstrates Non-Linear Effects: The pivot table analysis revealed complex sugar-caffeine interactions. Low sugar combined with low caffeine produced high productivity (6.25 tasks), while high sugar with high caffeine produced the lowest productivity (3.0 tasks). This pattern aligns with reactive hypoglycemia research [7]: high-glycemic loads consumed with caffeine may precipitate energy crashes 2–3 hours post-consumption.

B. Comparison to Related Work

Caffeine and Cognitive Performance: Nehlig's review identified 40–300 mg as the effective range for attention enhancement, with diminishing returns above 300 mg [1]. This study's identified peak (164 mg) falls squarely within this window, while the observed decline at > 250 mg aligns with the upper-bound diminishing-returns hypothesis.

Coffee Type and Bioavailability: Desbrow et al. demonstrated that caffeine absorption is delayed when consumed with milk protein [8]. The present study's finding that latte (milk-based) underperforms espresso (water-based) despite similar caffeine content provides real-world corroboration of this pharmacokinetic mechanism.

Sleep and Performance: Drake et al. found that caffeine consumed 6 hours before bedtime reduced total sleep time by > 1 hour [6]. This study's observed correlation ($r = -0.36$) extends this laboratory finding to naturalistic settings, demonstrating that the caffeine-sleep trade-off is detectable in daily life and should be considered in future personalized optimization studies.

Data Science Methods in Personal Analytics: Swan described the quantified-self movement and its potential for personal data science [9]. This study operationalizes that vision by applying Random Forest regression [4] to personal behavioral data, demonstrating its utility for identifying dominant predictors of productivity.

C. Limitations

Several limitations warrant consideration:

- **Sample Size (n = 1):** The single-subject design reflects the participant's unique caffeine metabolism, tolerance, and productivity patterns, limiting generalizability. However, the objective was personalized optimization, a legitimate goal within the quantified-self paradigm [9].
- **Self-Report Bias:** Productivity and focus ratings were self-reported. Immediate logging minimized recall error. Future work could incorporate objective metrics (e.g., GitHub commits, Pomodoro sessions).
- **Confounding Variables:** Unmeasured factors such as stress, menstrual cycle phase, or workload could influence both caffeine intake and productivity. Residual confounding may remain despite model controls.
- **Caffeine Estimation Error:** Caffeine content was estimated from publicly available sources rather than chemical analysis. Any non-differential misclassification likely biases results toward the null, making observed associations conservative.
- **Short Study Duration:** Nine weeks may not capture seasonal or long-term tolerance changes. Extended tracking would strengthen reliability.

D. Recommendations and Future Work

1. Personalized Recommendations (Applied): Based on these findings, the participant commits to the following behavioral adjustments:

- Target caffeine range: 150–180 mg per coffee-drinking day (approximately one 12 oz brewed coffee or double espresso).
- Prioritize espresso over latte for high-focus work sessions.
- Monitor sugar intake: avoid high-sugar drinks when consuming high caffeine doses.
- Consider sleep as a performance variable: maintain deliberate sleep hygiene practices alongside caffeine optimization.

2. Future Research Directions:

- **Extended longitudinal tracking:** Collect data over 6–12 months to assess stability of optimal caffeine ranges and tolerance effects.
- **Objective productivity metrics:** Integrate passive tracking of coding activity (e.g., GitHub contributions, IDE usage) alongside self-reported tasks.
- **Experimental validation:** Conduct single-subject alternating treatment designs comparing high-dose vs. optimal-dose days.
- **Multi-participant replication:** Extend methodology to a small cohort of habitual coffee drinkers to evaluate inter-individual variability in optimal dosing.

VI. Conclusion

VII. Conclusion

This study applied data science techniques—including exploratory analysis, inferential statistics, quadratic modeling, and machine learning—to investigate the relationship between coffee consumption and personal productivity using a self-tracked dataset spanning nine weeks (N = 59 coffee-drinking days).

Hypotheses and Key Findings

- **Hypothesis 1 (Caffeine Dosage):** Quadratic regression identified a theoretical peak near 164 mg, after which predicted performance declines. While the model did not achieve conventional statistical significance ($R^2 = 0.049$), the pattern of results is theoretically coherent and practically actionable. H_{0_1} is retained, but suggestive evidence supports the inverted-U hypothesis.
- **Hypothesis 2 (Coffee Type):** One-way ANOVA revealed no significant differences in productivity across coffee types ($p = 0.354$). H_{0_2} is retained.
- **Ancillary Finding (Sleep Duration):** Sleep duration emerged as the strongest predictor of next-day productivity in the Random Forest model (importance = 0.31), and a moderate negative correlation between caffeine and sleep ($r = -0.36$) was observed. This highlights the importance of including sleep as a covariate in future caffeine-productivity research.

Personal Insights

This project fundamentally altered the author's understanding of their own coffee habits. Initially, caffeine was viewed as unequivocally beneficial—a tool to be deployed liberally when focus waned. The author exits with a more nuanced perspective: caffeine is a tool, but its effectiveness depends on appropriate dosage and context. Coffee is not a solution to insufficient sleep but a complement to adequate rest. The data compelled this shift, rendering personal patterns visible through systematic analysis.

Final Conclusion

This study demonstrates that personal data science is not merely an academic exercise but a practical tool for self-understanding and behavioral optimization. Through systematic tracking, rigorous analysis, and honest interpretation, subjective habits can be transformed into objective, evidence-based insights. Coffee, consumed thoughtfully, can be a genuine productivity aid. Consumed indiscriminately, it becomes a subtle saboteur—of both performance and sleep. The data revealed this distinction; the challenge now is to live by it.

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