IDENTIFYING WEEKLY SPENDING CYCLES IN PERSONAL EXPENSE RECORDS

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***Abstract*—This study examined a student's spending behavior using a personal budget tracker aligned with weekly limits based on school allowance cycles. Daily expense and income entries were recorded in a spreadsheet, consolidated into eight categories (Personal, Food, Transportation, Savings, Utilities, School, Rent, Loan), and corrected using description-based rules to reduce mislabeling. The dataset covered 471 tracked days from September 2024 to February 2026. Python-based analysis produced descriptive statistics and visualizations, tested day-type differences via one-way ANOVA, evaluated pre–post scholarship changes with a paired t-test (3-day windows), and modeled daily expense using ordinary least squares regression with weekend, school-day, scholarship receipt, and days-since-income predictors. Spending was right-skewed, with infrequent high-cost spike days driving variance. Although Regular days showed the highest mean expense, ANOVA results indicated no statistically significant differences among School, Regular, and Weekend days. The paired t-test likewise found no significant change after scholarship receipt; however, regression results suggested higher same-day expenses on scholarship dates and lower spending as time since income increased. Overall, findings indicate that event-driven obligations and income timing, rather than calendar day type alone, best explain observed spending dynamics and can guide practical budgeting.**

***Index Terms*—Budget tracking, personal informatics, spending behavior, financial self-control**

I. INTRODUCTION

Personal behavior tracking has expanded rapidly with the availability of digital tools, such as spreadsheets, mobile applications, and self-logging platforms, that enable individuals to continuously record aspects of daily life. Within the broader practice of digital self-tracking, activities ranging from sleep and physical activity to mood and productivity are translated into structured data that can be visualized and analyzed over time [1]. Financial behavior, particularly daily spending, fits naturally within this paradigm. Expense trackers and spreadsheet-based logs transform routine purchases into time-stamped records, enabling individuals to observe how money use aligns with daily structure and obligations [2], [3]. Viewed through this lens, spending is not merely a financial ledger but a behavioral signal that reflects routines, constraints, and decision-making, much as sleep duration or work hours reveal underlying patterns in daily life.

Despite the availability of such tools, budgeting decisions are often guided by intuition rather than longitudinal evidence. Mental budgeting, such as organizing expenses internally without external records, is cognitively demanding and prone to shortcuts, leading individuals to rely on gut feelings when assessing affordability or progress toward goals [4]. Behavioral biases such as anchoring, overconfidence, and loss aversion further distort perceptions of spending and budget adjustment [5]. These issues can be amplified in contexts where financial decisions are made independently, such as living alone, where the absence of external feedback allows mood and perceived account balance to drive daily spending choices [6]. Prior work consistently shows that persistent expense tracking and clear feedback improve financial awareness, discipline, and literacy, particularly among students and young adults with constrained incomes [7], [8]. Understanding not only how much is spent but also when spending increases, across school days, weekends, or following income receipt, therefore, matters for improving personal financial planning and reducing reliance on inaccurate self-perception.

Existing research on personal finance systems and analytics, however, remains largely descriptive or predictive in nature. Many expense-tracking tools and studies emphasize visualization, categorization, and trend summaries, yet they do not formally test whether observed differences across days or events are statistically meaningful [3], [9]. More advanced work applies machine learning to cluster users or infer psychological traits and financial literacy levels, often using cross-sectional data and population-level models [10], [11], [12]. While informative, these approaches rarely examine routine-based temporal structures, such as school days versus weekends, or treat income receipt as a behavioral event at the individual level. Reviews of student money management similarly document budgeting and borrowing behaviors but note the lack of attention to habitual, non-reflective processes tied to time and routine [13], whereas financial planning theory emphasizes mental accounting across income types rather than temporal spending cycles [14]. As a result, there is a clear gap in within-subjects statistical analyses that test how daily spending varies across routine contexts and short post-income periods. Addressing this gap motivates the present study, which frames personal expense data as a longitudinal behavioral signal and applies formal hypothesis testing to evaluate routine- and event-driven spending patterns.

A. Objectives of the Study

1) General Objective: To examine personal daily spending as a longitudinal dataset and determine whether statistically meaningful variation is associated with (a) routine day types and (b) short-term income receipt events within weekly allowance cycles.

2) Specific Objectives:

- To determine whether there are statistically significant differences in mean daily expenses across school days, regular days, and weekends.
- To evaluate whether daily spending changes significantly during the short period following income receipt by comparing pre-income and post-income spending.
- To interpret observed spending patterns in relation to routine structure and income-related decision-making to support evidence-based personal financial planning.

B. Research Questions

1) Is there a statistically significant difference in mean daily spending across school days, regular days, and weekends?
2) Does daily spending change significantly after a sudden additional income is received?

This work is a within-subject case study intended to support evidence-based personal budgeting rather than population-level generalization. The study's value lies in converting routine expense tracking into tested insights: distinguishing stable behavior from spike-driven variability, identifying high-risk spending contexts, and improving budgeting strategy through event planning rather than intuition.

II. Literature Review

A. Personal Behavior Tracking and Expense Monitoring

Prior studies on personal behavior tracking have established that routine self-logging, whether of sleep, mood, productivity, or finances, transforms everyday actions into analyzable behavioral data. In the financial domain, expense-tracking applications and financial logging systems primarily analyze transaction-level records, including income, expenses, categories, and timestamps, often collected via mobile apps or spreadsheets [3], [8], [15]. These systems rely on descriptive analytics, including category summaries, time-series charts, and weekly or monthly dashboards, to provide users with visibility into their spending patterns. Empirical evaluations consistently report improved financial awareness, perceived control, and reduced stress among users who engage in continuous expense tracking [8], [16]. However, while these tools successfully reveal what money is spent on and how much is spent over time, they largely stop short of testing whether observed differences across days or periods represent statistically meaningful behavioral patterns.

B. Behavioral and Temporal Analysis of Data

Beyond finance, behavioral research has demonstrated that temporal cycles play a central role in structuring human activity. Studies in productivity, sleep, and time-use analysis routinely examine daily and weekly rhythms, showing that routines anchored to weekdays, weekends, and recurring obligations shape behavior and performance [17]. In organizational and personal contexts, temporal structures such as deadlines, milestones, and self-imposed schedules act as mechanisms of "temporal self-discipline," aligning behavior with planned goals but remaining vulnerable to disruption by unexpected events [18]. Mental budgeting research further supports the importance of temporal framing, showing that people naturally allocate resources to time-bound windows (e.g., weekly or daily budgets), and that shorter temporal frames can reduce perceived affordability and curb spending under certain conditions [19]. Despite this growing recognition of time as a behavioral organizing principle, its application to personal finance remains coarse, with most systems operating at monthly or weekly resolutions and offering limited insight into how specific routine contexts or income events shape daily spending decisions [14], [20].

C. Synthesis

Across the literature, several recurring limitations emerge. First, many studies rely on aggregated or population-level data, emphasizing cross-sectional comparisons or user segmentation rather than within-person longitudinal analysis [10], [12], [13]. Second, advanced methods such as machine learning and clustering are often used to infer financial literacy, personality traits, or risk profiles, but these approaches prioritize prediction over causal or inferential understanding of routine-driven behavior [9], [10], [11], [12]. Third, although expense trackers and budgeting applications embed temporal cycles through daily logging and weekly or monthly summaries, they rarely isolate or test the behavioral impact of specific temporal contexts, such as school days versus weekends or pre- versus post-income periods [8], [16]. As a result, much of the existing work remains descriptive, visually informative, or predictive, with limited use of formal hypothesis testing to assess the statistical robustness of observed temporal variations in spending.

The present study builds on this body of work by treating personal expense data as a longitudinal behavioral signal rather than a static financial record. Unlike prior studies that emphasize visualization, aggregation, or population-level inference, this research applies statistical hypothesis testing to a within-subjects expense dataset to examine differences in routine-based spending across school days, regular days, and weekends, as well as short-term changes in spending following income receipt. By focusing on temporal routines and income events at the individual level, the study addresses a documented gap in personal finance research concerning when spending behavior systematically changes. In doing so, it contributes a methodologically distinct perspective that complements existing descriptive and predictive approaches, demonstrating how inferential analysis can support evidence-based personal financial planning rather than reliance on intuition alone.

III. Methodology

A. Participants

The participant in this study was the student researcher, who served as the sole subject of the analysis under a within-subject observational design. The study focused on longitudinal spending behavior rather than population-level generalization. The participant falls within the young adult age range and is a full-time undergraduate student whose routine academic obligations structure daily activity into school days, regular weekdays, and weekends.

B. Data Collection

This study employed structured manual logging to capture daily expense transactions and event-based income receipts using a spreadsheet environment (Google Sheets). Each expense record included the transaction date, amount in Philippine pesos (PHP), a category label, and a brief description of the purchase, while each income record contained the receipt date, amount (PHP), income category, and a short description. To reduce recall bias and minimize missing entries, expenses were logged on the same day the transaction occurred; when same-day logging was not feasible, delayed entries were encoded as soon as possible and cross-validated using available personal references such as message confirmations, purchase notes, and routine spending patterns. Prior to analysis, selected sensitive expense entries were removed to protect privacy, without altering the broader structure of the dataset used for statistical procedures.

The final dataset covered the period from September 1, 2024 to February 7, 2026, enabling month-level and week-level comparisons of spending behavior across the observation window. For income, two allowance streams were included in the analysis: (1) School Allowance, a predictable baseline income cycle provided as a fixed amount, and (2) Scholarship Allowance, an irregular and occasionally bulk-received stream treated as an "income shock" event to support pre–post behavioral comparisons. In contrast, bill-specific allowances were recorded separately and excluded from the discretionary income calculation to avoid overstating overspending when evaluating day-to-day spending patterns.

To support routine-based comparisons, each calendar date in the dataset was assigned a day-type label. Day type was defined as School Day, Regular Day, or Weekend based on the participant's academic schedule. This classification was treated as a derived variable used for grouping and hypothesis testing.

C. Operational Definitions

1) Precise Definitions of each variable:

- Expenses Date: The calendar date on which an expense transaction occurred.

TABLE I
VARIABLES, TYPES, UNITS/SCALES, AND LOGGING FREQUENCY

Variable	Type	Unit/Scale	Frequency
Expenses Date	Qualitative	Date	Per expense entry
Expenses Amount	Quantitative	PHP (ratio)	Per expense entry
Expenses Description	Qualitative	Text	Per expense entry
Expenses Category	Qualitative	Nominal categories	Per expense entry
Income Date	Qualitative	Date	Per income entry
Income Amount	Quantitative	PHP (ratio)	Per income entry
Income Description	Qualitative	Text	Per income entry
Income Category	Qualitative	Nominal categories	Per income entry
Day Type	Qualitative	Nominal categories	Per expense entry

- Expenses Amount: The monetary value of an individual expense transaction, measured in Philippine pesos (PHP).
- Expenses Description: A brief text entry describing the purpose or nature of an expense transaction.
- Expenses Category: A categorical label assigned to each expense transaction to classify the type of spending (e.g., food, transportation, personal).
- Income Date: The calendar date on which an income transaction was received.
- Income Amount: The monetary value of an income transaction, measured in Philippine pesos (PHP).
- Income Description: A brief text entry describing the source or purpose of an income transaction.
- Income Category: A categorical label assigned to each income transaction to classify the type of income received.
- Day Type: A derived categorical variable that classifies each date based on routine structure, where school days correspond to days with scheduled academic activities, regular days refer to non-school weekdays, and weekends correspond to Saturdays and Sundays.

2) Derived variables:

- Daily Expense: Total expenses aggregated per day (sum of expense transactions per date).
- Daily Income: Total income aggregated per day (sum of income transactions per date).
- Scholarship Received (0/1): Indicator that a scholarship allowance was received on that date (treated as an income shock).
- Days Since Last Income: Count of days since the most recent income receipt event.
- Expense Income Ratio: The ratio between weekly expenses and weekly income.
- Post-Scholarship Window: an indicator for the first three days following scholarship receipt.

D. Data Cleaning

Data preprocessing was performed in Python (Pandas) prior to analysis to ensure consistency and reduce measurement noise.

Date parsing and standardization: Transaction dates were converted into a consistent *datetime* format to enable reliable daily and weekly aggregation. Entries with missing, malformed, or invalid dates were excluded to prevent incorrect grouping.

Numeric conversion and unit consistency: Amount fields were standardized into numeric values for accurate summation and statistical computation. Non-numeric artifacts (e.g., commas) were removed prior to conversion to avoid parsing errors and incorrect totals.

Description-based category correction: Since categories were manually assigned, some entries were potentially mislabeled. To reduce systematic noise, category labels were cross-validated using the transaction description. When descriptions contained strong category cues (e.g., rent keywords, transport keywords, tuition markers), targeted recoding rules were applied to reassign entries into the standardized category set. Corrections were limited to clearly defined keyword rules to avoid overcorrection.

Category consolidation and correction: Category consolidation was performed by mapping raw tracker labels—including bill-specific and week-labeled entries—into an eight-category scheme (Personal, Food, Transportation, Savings, Utilities, School, Rent, Loan). To reduce mislabeling from manual assignment, a rule-based review of descriptions was applied to flag entries containing strong cues (e.g., rent keywords, tuition markers, transport terms) and recode them into the standardized set. Post-cleaning checks were conducted using category counts and targeted description review to confirm consistency.

Missing values and outliers: Missing descriptions were retained because they did not affect numeric aggregation. Daily spending outliers were flagged for documentation and interpretation rather than automatically removed, since high-cost days may represent valid behavioral events.

E. Statistical Analysis

Analyses were conducted in Python using SciPy, StatsModels, and Matplotlib to address both research questions and secondary behavioral metrics.

Descriptive statistics: Daily expenses were aggregated by date, then summarized using mean, median, standard deviation, minimum, maximum, and count (n). The same summaries were also computed per Day_Type (School, Regular, Weekend).

Data visualization: Spending behavior was visualized using a histogram (distribution and outliers), a time-series plot of daily expenses (trend/volatility, optional rolling mean), a bar chart of mean expense by Day_Type (with variability markers), and a correlation heatmap for numeric variables.

Hypothesis testing: Day_Type differences were tested using one-way ANOVA (School vs Regular vs Weekend), reporting F, p, and eta-squared (^{2}) at = 0.05. Spending changes around scholarship income events were tested using a paired t-test comparing mean daily expense in three-day before/after windows, reporting mean difference, t, p, and Cohen's d at = 0.05. Post-hoc testing (e.g., Tukey HSD) was planned only if ANOVA was significant.

Correlation analysis: Pearson correlations were computed between daily expenses and key numeric predictors and summarized using a correlation matrix and heatmap. Correlations were interpreted as associations, not causation.

Regression modeling: Ordinary Least Squares (OLS) regression modeled Daily Expense from day-type indicators and income-timing features (including a post-scholarship window), with robust standard errors to account for heteroscedasticity and short-run autocorrelation.

F. Assumptions, Bias, and Measurement Error Considerations

Given the nature of personal spending data, several assumptions and potential sources of bias were considered in the analysis. Daily expense values may exhibit skewness, particularly when infrequent high-cost purchases occur, which can affect normality assumptions underlying parametric tests. As such, distributional characteristics were examined prior to hypothesis testing, and results were interpreted with attention to robustness rather than strict normality.

The study also acknowledges the possibility of measurement error arising from manual data entry. Delayed logging or unrecorded transactions may lead to underestimation of daily spending totals, particularly on busy or atypical days. Additionally, the classification of day type relies on the accuracy of the participant's academic schedule; any misclassification of school days, regular days, or weekends may reduce separation between comparison groups and attenuate observed effects.

To mitigate these risks, the dataset was maintained using consistent daily logging practices, standardized expense categories, and routine validation checks during preprocessing. All findings are interpreted within the constraints of a single-subject observational design and are intended to reflect individual behavioral patterns rather than population-level financial behavior.

Group sizes across day types were not equal because the participant's schedule produced more school days than weekends within the recorded period. This imbalance may reduce statistical power for detecting differences across day types and increases sensitivity to outliers within smaller groups.

IV. Results

A. Dataset Overview

Across the full tracking period, the dataset captured 1,204 expense entries and 312 income entries, spanning September 1, 2024 to February 7, 2026. In total, 471 days were logged, accumulating PHP 533,937 in recorded expenses, establishing a sufficiently long window to observe both routine spending and occasional spikes.

Daily spending showed a wide range, with a minimum of PHP 15 and a maximum of PHP 15,068, indicating that the same tracker captured both low-cost days and high-impact spending events. The mean daily expense was PHP 1,124.08, while the median was substantially lower at PHP 570.00, suggesting a right-skewed distribution in which a smaller number of expensive days increases the average. This pattern is reinforced by the standard deviation of PHP 1,861.11, which exceeds the mean, indicating high variability rather than steady, uniform spending.

TABLE II
OVERALL SUMMARY METRICS

Metric	Value
Total expense entries	1,204
Total income entries	312
Date range	2024-09-01 to 2026-02-07
Total days tracked	471
Total expenses (PHP)	533,937.00
Min daily expenses (PHP)	15.00
Max daily expenses (PHP)	15,068.00
Mean daily expense (PHP)	1,124.08
Median daily expense (PHP)	570.00
SD daily expense (PHP)	1,861.11
Q1 (25th pct) daily expense (PHP)	346.00
Q2 (50th pct / median) daily expense (PHP)	570.00
Q3 (75th pct) daily expense (PHP)	932.00
IQR (Q3 - Q1) daily expense (PHP)	586.00
Percentile rank of mean daily expense	81.05
Percentile rank of median daily expense	50.11

Quartile estimates further contextualize the distribution. The middle 50% of days fell between PHP 346.00 (Q1) and PHP 932.00 (Q3), yielding an interquartile range (IQR) of PHP 586.00. Thus, spending on a typical day remained within a relatively bounded range, while infrequent extreme values substantially expanded the overall spread. Consistent with this, the mean corresponded to approximately the 81st percentile of daily expenses, whereas the median aligned near the 50th percentile, emphasizing that the "average day" differs from the "typical day" in this dataset.

B. Distribution of Daily Expenses

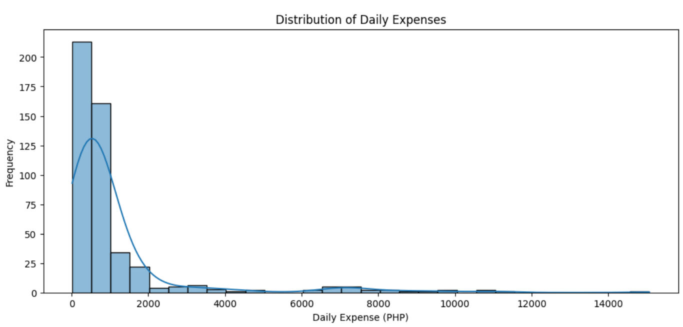

Fig. 1. Distribution of Daily Expenses

Figure 1 shows that daily expenses are strongly right-skewed, with most days concentrated in the lower spending ranges (roughly below PHP 1,000–2,000) and a long tail extending toward high-cost days. This indicates that routine, low-to-moderate spending dominates the tracking period while a smaller set of "big spend" days occurs sporadically. This pattern is confirmed quantitatively by the skewness of 3.8119, reflecting a heavy pull to the right, and the kurtosis of 16.1362, indicating a sharp peak with unusually heavy tails (i.e., extreme values occur more often than would be expected under a normal distribution). As a result, a few high-expense events exert outsized influence on the overall average, helping explain why the mean sits notably above the median.

C. Time-Series Trend of Spending

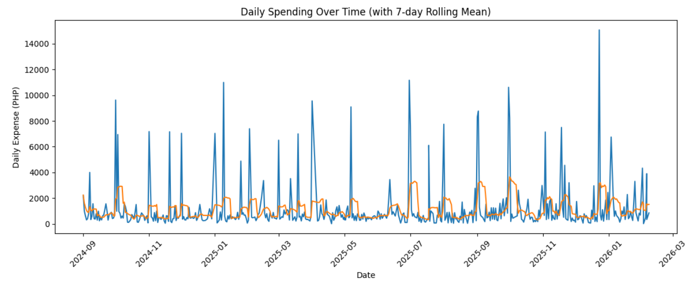

Fig. 2. Time Series of Daily Spending (September 2024 onward)

Figure 2 shows that daily spending was generally maintained at a low-to-moderate baseline but was repeatedly disrupted by sharp, isolated spikes that reached as high as approximately PHP 15,000, indicating irregular high-expense days throughout the period. This after the 7-day rolling mean (orange line) reveals short waves of elevated spending—suggesting brief high-cost stretches rather than a steady long-term upward trend—before repeatedly settling back toward the usual range.

D. Core Weekly Structure per Day Type

TABLE III
MEAN, MEDIAN, SD OF DAILY SPENDING BY DAY_TYPE

Day_Type	Mean (PHP)	Median (PHP)	SD (PHP)	Count (days)
Regular	1,360.13	655.00	2,226.95	137
School	1,038.98	559.00	1,779.67	233
Weekend	1,004.92	540.00	1,460.17	105

The table shows that Regular days recorded the highest daily spending level (M = PHP 1,360.13; Md = PHP 655.00) and the greatest dispersion (SD = PHP 2,226.95) compared with School days (M = PHP 1,038.98; Md = PHP 559.00; SD = PHP 1,779.67) and Weekends, which posted the lowest mean (M = PHP 1,004.92; Md = PHP 540.00; SD = PHP 1,460.17). This after all three groups still exhibited relatively large standard deviations, implying substantial within-group variability and likely overlap in daily spending amounts across day types despite the differences in average levels.

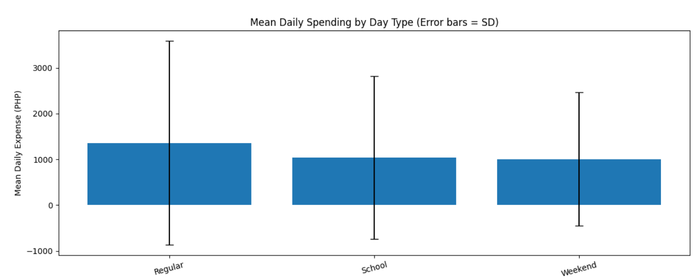

Fig. 3. Mean Daily Spending by Day Type

Figure 3 displays the mean daily expense across school days, regular days, and weekends, with error bars representing the standard deviation (SD). Regular days show the highest mean expense, while school days and weekends have lower and similar means; however, the SD bars are wide and substantially overlapping across all groups, indicating high within-group variability and limited visual separation of group means in this descriptive comparison. The relatively larger dispersion, particularly for regular days, suggests greater spread of daily expenses within that group. Because outliers were retained, the means and SDs reflect the full distribution of observed spending values, including extreme observations.

TABLE IV
DAY_TYPE GROUP COMPARISON TESTS (DAILY_EXPENSE)

Test	Stat.	p	Decision ($\alpha = 0.05$)	η^2
Levene (median)	1.4302	0.240307	Equal variances plausible	–
ANOVA	1.5644	0.210287	Fail to reject H_0	0.0066
Kruskal–Wallis	3.1320	0.208883	Fail to reject H_0	–

Variance across day types appeared comparable, as the median-centered Levene test was not significant (statistic $= 1.4302$, $p = 0.2403$; $\alpha = 0.05$), making the equal-variance assumption plausible for group comparison. Building on this, the one-way ANOVA found no statistically significant difference in mean daily expenses across *Day_Type* ($F = 1.5644$, $p = 0.2103$), leading to a fail-to-reject decision at $\alpha = 0.05$; importantly, the effect size was very small ($\eta^2 = 0.0066$), suggesting that day type explains less than 1% of the variance in daily spending. Consistent with the parametric result, the Kruskal–Wallis test—used as a distribution-robust alternative given the skewed nature of expenses—also showed no significant difference in spending distributions across day types ($H = 3.1320$, $p = 0.2089$), reinforcing the interpretation that, within this dataset, spending behavior does not materially shift between School, Regular, and Weekend days.

E. Category Behavior

TABLE V
TOTAL EXPENSES AND SHARE OF TOTAL BY CATEGORY

Expenses_Category	Total (PHP)	Percent_of_Total (%)
Food	149,173	27.94
Personal	107,406	20.12
Rent	101,834	19.07
School	68,755	12.88
Transportation	39,848	7.46
Utilities	31,563	5.91
Loan	29,385	5.50
Savings	5,973	1.12

This category summary indicates that spending is concentrated in a few major components. Food accounts for the largest share at 27.94% of total expenses (PHP 149,173), followed by Personal at 20.12% (PHP 107,406) and Rent at 19.07% (PHP 101,834), meaning these three categories alone comprise 67.13% of overall recorded spending. Mid-tier contributors include School at 12.88% (PHP 68,755) and Transportation at 7.46% (PHP 39,848), while Utilities and Loan contribute 5.91% (PHP 31,563) and 5.50% (PHP 29,385), respectively. Savings represents the smallest recorded portion at 1.12% (PHP 5,973). , indicating that only a limited fraction of recorded outflows was directed toward formal saving within the observed period.

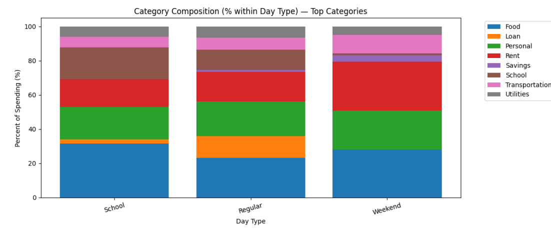

Fig. 4. Stacked Bar Chart of Category % by Day_Type

Figure 4 summarizes the within-day-type composition of expenses and shows clear shifts in dominant categories across School, Regular, and Weekend days. School days are characterized by a larger allocation to Food and a substantial share for School-related spending, whereas Regular days exhibit a more diversified profile in which Food and Personal remain major components but Loan expenses constitute a visibly larger proportion than in the other day types. In contrast, Weekend spending is driven primarily by Rent and Food, with smaller contributions from Utilities, Transportation, and Savings, indicating that weekend outflows are more concentrated in fixed or recurring cost categories rather than school-driven expenditures.

F. Income Shock Analysis

Scholarship allowance receipts were treated as "shock dates" because they represent discrete, externally timed cash inflows that could plausibly trigger immediate changes in spending behavior beyond routine daily patterns. Other allowances (e.g., utilities allowances) were excluded because they are typically earmarked for specific bills, may be paid directly or intended for predetermined obligations, and therefore do not function as comparable "free-to-allocate" income shocks that would reflect general discretionary spending responses. For each scholarship shock date, mean daily spending was computed for the three days before and three days after the receipt to isolate short-run effects while minimizing contamination from longer-term trends, weekly cycles, or one-off anomalies through day-to-day averaging.

TABLE VI
PRE–POST SCHOLARSHIP SPENDING TESTS

Test	n	Stat.	p	α	Mean Diff	d	95% Boot CI
Paired t-test	54	$t = -0.6908$	0.492683	0.05	-143.82	-0.0940	$[-559.73, 265.65]$
Wilcoxon signed-rank	54	$W = 742.0$	0.996565	0.05	–	–	–

Decision: Both tests fail to reject H_0. Wilcoxon median difference (After–Before) $= 83.83$.

Across 54 scholarship events, the analysis did not show evidence that daily spending meaningfully changed after scholarship receipt: the paired t-test was non-significant ($t = -0.6908$, $p = 0.4927$, $\alpha = 0.05$), so the null hypothesis was not rejected. While the estimated mean difference (After–Before) was -143.82 (a slight decrease), the effect was negligible (Cohen's $d = -0.0940$), and the bootstrap 95% confidence interval crossed zero (-559.73 to 265.65), indicating that the change is not statistically reliable. Consistent with this, the Wilcoxon signed-rank test also found no significant shift in spending ($W = 742.0$, $p = 0.9966$, $\alpha = 0.05$), again failing to reject the null hypothesis, with a median difference of 83.83 suggesting mixed directionality across events rather than a systematic post-scholarship pattern. Taken together, both mean- and median-based tests point to the same conclusion that scholarship receipt alone was not associated with a detectable change in spending within the defined before/after window for this dataset.

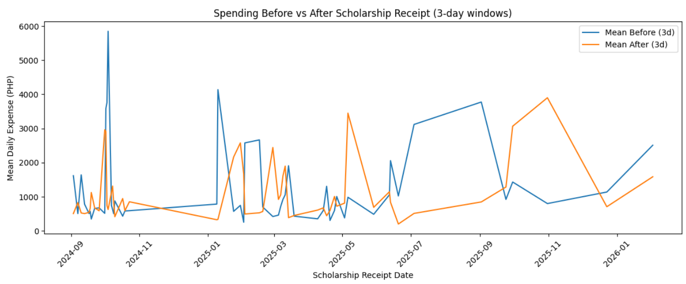

Fig. 5. Spending Before vs After Scholarship Receipt (3-day windows)

The 3-day window comparison shows that mean spending before and after scholarship receipt fluctuated considerably across events, with the two series frequently intersecting and no consistent post-receipt increase or decrease. Across multiple scholarship dates, some instances exhibit higher "after" averages while others show higher "before" averages, indicating that short-term spending responses were heterogeneous and dominated by event-specific volatility rather than a systematic shift attributable to scholarship receipt. This visual pattern aligns with the paired t-test results for the 3-day windows, reinforcing the conclusion that scholarship receipt was not associated with a statistically detectable change in immediate spending levels.

G. Expense-Income Ratio

Fig. 6. Weekly Expense-Income Ratio Over Time

The figure plots the weekly expense–income ratio across the tracking period to show how closely spending aligned with cash inflows week by week. The series stays clustered near the break-even line for most weeks, indicating that weekly spending was generally kept within the range of weekly income; however, the pattern is not a smooth trend and instead shifts in bursts, tight stretches of control followed by sudden surges, suggesting that budgeting performance was shaped more by event weeks than gradual drift. The pronounced spikes mark weeks where expenses clearly outpaced income, consistent with one-off or "lumpy" costs (e.g., bill payments, bulk purchases, or unexpected obligations) that can tilt an otherwise balanced week into overspending, while the troughs reflect periods of conservative spending and/or stronger inflows where discretionary expenses were better contained. The visible breaks in the sequence correspond to weeks with no recorded income, where the ratio is undefined and should be interpreted as a limitation of the metric rather than a behavioral shift. Overall, the figure supports a "mostly stable, occasionally volatile" spending profile: the baseline sits near balance, but budgeting discipline is most stressed during specific weeks that trigger sharp deviations.

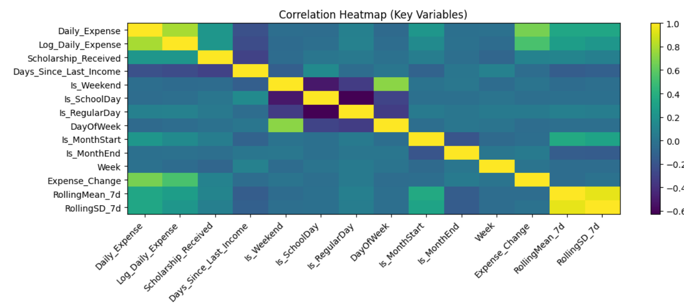

Fig. 7. Correlation Heatmap on Key Variables

The correlation heatmap suggests that daily spending moves most closely with its log-transformed counterpart and with short-term spending shifts (expense change), indicating that days with higher outlays tend to coincide with sharper day-to-day movement rather than a slow, linear drift. Weekly dynamics also show up: both the 7-day rolling mean and rolling variability track alongside daily expense, implying that when the baseline level of spending rises, week-level volatility often rises with it as well. Scholarship receipt shows a small positive relationship with spending, but its association is noticeably weaker than the effect captured by short-term change and rolling behavior, hinting that allowance inflows may nudge expenses without fully dictating day-to-day decisions. In contrast, days since the last income is inversely related to spending and to scholarship receipt, consistent with a tightening pattern as the gap from the last inflow widens. Calendar structure appears secondary: weekend, school day, regular day, and day-of-week indicators exhibit minimal direct links to spending, while month-start shows a modest connection with elevated rolling patterns, suggesting light clustering around reset periods rather than strong weekday-driven habits. Finally, several engineered timing features align strongly with each other (e.g., rolling mean with rolling variability, and weekend with day-of-week), reinforcing that these variables capture overlapping rhythms and should be interpreted as complementary signals rather than independent drivers.

H. Regression Model

TABLE VII
OLS REGRESSION RESULTS

Predictor	Coef	SE	p
Intercept	840.9220	270.215	0.002
School (vs Regular)	-305.8524	229.336	0.182
Weekend (vs Regular)	-342.5114	243.212	0.159
PostScholarship_3d	664.4967	237.792	0.005
t	1.1432	0.630	0.069

The OLS model regresses `Daily_Expense` on day type (School and Weekend vs. baseline Regular), a short post-scholarship window (first 3 days), and a time index (t), using HAC-robust standard errors (3 lags) to account for heteroscedasticity and short-run autocorrelation. Overall fit is modest ($R^2 = 0.033$; Adj. $R^2 = 0.025$), meaning the predictors explain only a small portion of day-to-day spending variation even though the model is jointly significant (F-test $p = 0.0395$).

At baseline (Regular day, not in the 3-day post-scholarship window, at $t = 0$), expected spending is PHP 840.92 (SE = 270.22, $p = 0.002$; 95% CI: 311.31 to 1370.54). Relative to Regular days, School days are estimated at PHP 305.85 lower (SE = 229.34), but this difference is not statistically significant ($p = 0.182$; 95% CI: -755.34 to 143.64), and Weekend days are similarly PHP 342.51 lower (SE = 243.21) with no significant separation ($p = 0.159$; 95% CI: -819.20 to 134.18). Thus, day-type effects trend downward but remain uncertain.

The strongest signal emerges immediately after scholarship receipt: being in the first three days post-scholarship is associated with an average PHP 664.50 increase in daily expense (SE = 237.79, $p = 0.005$; 95% CI: 198.43 to 1130.56), indicating a short, measurable spending bump when funds arrive. The time index suggests only a marginal upward drift (PHP 1.14 per unit t, SE = 0.63, $p = 0.069$; 95% CI: -0.09 to 2.38).

V. DISCUSSION

A. Interpretation of Results

Across 471 tracked days (1,204 expense entries), spending showed a "low baseline, occasional spike" profile: the median daily expense (PHP 570) sat far below the mean (PHP 1,124), and the maximum day (PHP 15,068) pulled the distribution into a strong right skew, indicating that discipline is not continuously broken, it is periodically stress-tested by lumpy, high-impact events. Day type did not produce a statistically meaningful shift in daily spending: although Regular days had the highest mean (PHP 1,360) compared with School (PHP 1,039) and Weekend (PHP 1,005), variability was large and overlapping, and both ANOVA and Kruskal–Wallis failed to reject the null, with a very small effect size ($\eta^2 = 0.0066$), implying that the calendar label explains less than 1% of variance in day-to-day expenses. This suggests the participant's routine is not governed by "weekend spending rules" as a primary driver; instead, spending is shaped by what obligations land on which days, not what the day is called. Scholarship receipt did not produce a consistent pre–post change within the 3-day window: the paired t-test and Wilcoxon test were non-significant, effect size was negligible, and the bootstrap interval crossed zero, pointing to heterogeneous responses rather than a stable "after allowance = higher spending" pattern. Yet the regression results add an important value: controlling for day type and time, the post-scholarship window was positively associated with higher spending (PostScholarship_3d $\approx$ +PHP 664, $p = 0.005$), while the day-type coefficients remained non-significant and the time trend was only marginal, with overall fit modest (Adj. $R^2 \approx 0.025$). Taken together, the cleanest behavioral read is that spending changes are not reliably explained by weekday/weekend structure; instead, income timing and clustered obligations appear to be the real "gravity wells" of the budget, where the tracker's weekly limits are most likely to be challenged.

B. Comparison to Related Work

The results align with research describing expense logging as a mechanism for increasing awareness of cost drivers and routines, because the dataset structure (timestamps, categories, descriptions) reflects common self-tracking systems and supports sensemaking beyond memory-based budgeting. At the same time, this study reinforces a documented gap in the literature: many tools stop at descriptive summaries, while inferential testing can show that "visible differences" (e.g., weekends seeming higher) may not survive variance and spike-driven noise in real spending streams. The non-significant day-type finding also pushes back against a popular expectation that weekends reliably inflate discretionary spending; in a student context with bounded discretionary capacity and large fixed costs (rent, school payments) that can occur on any day, calendar effects can be masked. Finally, the income-timing association is consistent with temporal framing and mental accounting perspectives: income arrival can function less like a "spend now" trigger and more like a scheduling anchor for obligations and catch-up purchases, while spending tightens as time since last inflow increases.

C. Limitations

This self-experiment is valuable as a within-subject behavioral case, but its conclusions should be interpreted within several constraints:

- **Single-subject design ($n = 1$).** The results describe one participant's behavior and cannot be generalized to broader student populations without replication.
- **Self-report and logging bias.** Manual entry may miss transactions, compress multiple purchases into one entry, or shift dates when logging is delayed. Even with validation practices, underreporting may occur on busy or atypical days.
- **Category mislabeling risk.** Although description-based recoding was performed, rule-based corrections can

still misclassify edge cases, and classification noise can weaken observed relationships between context and spending.

- **Non-independence and heavy-tailed spending.** Daily expenses are strongly right-skewed with spike days, which can reduce the sensitivity of parametric tests and inflate variance. This may contribute to null results in day-type comparisons.
- **Income-event definition and windowing.** Scholarship receipt was treated as a "shock," but the behavioral meaning of a shock may vary across events (e.g., delayed bills, planned purchases, or catch-up spending). Heterogeneity across events reduces the likelihood of a consistent pre-post effect.

D. Recommendations and Future Work

Several improvements can strengthen future versions of this work and expand its usefulness to other students:

- **Add budget-intent variables.** Beyond recording spending, future logs can include whether a purchase was "planned" versus "impulsive," the trigger (e.g., hunger, convenience, social event), and perceived necessity. This would directly connect observed spikes to behavioral drivers.
- **Use an "obligation tagging" layer.** Fixed costs (rent, tuition, utilities) can be tagged as obligations, allowing analyses to test whether day-type effects emerge after separating obligations from discretionary expenses.
- **Model with robust methods.** Given skewness and spikes, future analyses can include robust regression or nonparametric comparisons for day-type differences, and event-study designs for income shocks.
- **Extend to multi-person replication.** A small cohort of students using the same tracker structure could preserve the behavioral focus while enabling comparisons across financial contexts, schedules, and allowance structures.
- **Strengthen compliance tracking.** A simple "missing-day indicator" and periodic reconciliation (e.g., weekly review of receipts or e-wallet history) could quantify logging completeness and reduce bias.

VI. Conclusion

This study examined a student's personal daily spending as a longitudinal behavioral dataset aligned with weekly limits based on school allowance cycles, using spreadsheet logging and Python-based analysis to test whether spending varies across routine day types and short post-scholarship income windows. Across 471 tracked days from September 2024 to February 2026, spending was characterized by a low typical baseline punctuated by infrequent high-cost spikes, producing a strongly right-skewed distribution in which a small number of "big spend" days meaningfully shaped variance. Inferential results indicated that mean spending did not differ significantly across School, Regular, and Weekend day types, suggesting that the calendar label of the day is not, by itself, a reliable driver of daily expense levels within this dataset. Scholarship receipt likewise did not yield a statistically reliable average pre–post shift in the defined short window; however, regression results suggested higher spending within the scholarship-related period and a pattern of tightening as time since the last income increased, consistent with temporally structured budgeting behavior and the clustering of obligations near inflow events.

From a personal standpoint, the findings suggest that expense tracking provided a clear view of how spending was shaped less by the calendar label of the day and more by event-driven obligations and income-timing constraints. Practically, these insights support an actionable conclusion: improving financial discipline may depend more on anticipating and smoothing high-cost events (e.g., rent, school payments, clustered obligations) than on relying solely on weekday/weekend rules. In terms of the participant's financial discipline, the pattern observed is best described as generally controlled day-to-day spending punctuated by episodic pressure points; a routine that holds steady on typical days but becomes vulnerable when large obligations cluster near income receipt periods, where spending is more likely to rise. This indicates that the participant's discipline is not primarily a problem of consistent overspending but of managing timing and planning around predictable spikes, highlighting the value of proactive allocation (setting aside funds ahead of due dates) over reactive adjustments after expenses occur. While limited by a single-subject observational design and self-report constraints, the study demonstrates how inferential methods can complement descriptive expense tracking to support evidence-based personal budgeting rather than intuition alone.

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