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, with total expenses of PHP 533,937 and total income of PHP 553,428. 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 behavioral dataset and determine whether statistically significant variations in mean expenses are associated with routine day types (school days, regular days, and weekends) and short-term income receipt events.

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?

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 (PHP 2,500 during the early months and later increased to PHP 3,000), 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.
- 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.

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 (e.g., IQR-based) 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 (e.g., income indicators, days since last income, week index) and summarized using a correlation matrix and heatmap. Correlations were interpreted as associations, not causation.

Regression modeling: Multiple linear regression (OLS) modeled daily expense totals as a function of *Day_Type* (dummy-coded) and income-timing variables (e.g., income receipt indicators and days since last income). Outputs included β coefficients, standard errors, p-values, and model fit metrics (R^2 and adjusted R^2).

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. Interpretation of Findings

B. Dataset Overview

TABLE I
SUMMARY STATISTICS OF TRACKED EXPENSES AND INCOME

Metric	Value
Total number of expense entries	1,204
Total number of income entries	312
Date range	2024-09-01 to 2026-02-07
Total days tracked	471
Total expenses (PHP)	533,937.00
Total income (PHP)	553,428.00
Mean daily expense (PHP)	1,124.08
Median daily expense (PHP)	570.00
Standard deviation of daily expense (PHP)	1,861.11

The dataset captured 1,204 expense entries and 312 income entries across the monitoring period.

This was after tracking personal finances from September 1, 2024, to February 7, 2026, spanning 471 days of recorded activity. Over this period, total spending reached PHP 533,937.00, while total income amounted to PHP 553,428.00, resulting in a slight overall cash inflow within the observed window.

On a day-to-day basis, expenses averaged PHP 1,124.08 per day, but the median daily expense of PHP 570.00 indicates that a typical day involved noticeably lower spending than the mean. This gap between the mean and median suggests that higher-cost days pulled the average upward rather than representing the most common daily pattern.

This pattern is reinforced by the standard deviation of PHP 1,861.11, showing wide variability in daily expenses. In practice, spending behavior was not consistent across days; instead, it was shaped by occasional high-expense days that created larger swings in the daily totals.

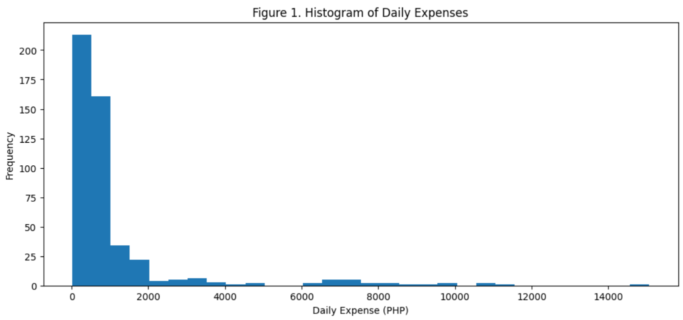

Fig. 1. Histogram of Daily Expenses

C. Distribution of Daily Expenses

Figure 1 shows that daily expenses are strongly right-skewed, with most days clustered at low spending levels and frequencies dropping quickly as costs increase. This after a small number of high-expense spike days extend the distribution into a long tail reaching roughly PHP 15,000, indicating that occasional large transactions—rather than typical daily spending—drive much of the variability in the dataset.

D. Time-Series Trend of Spending

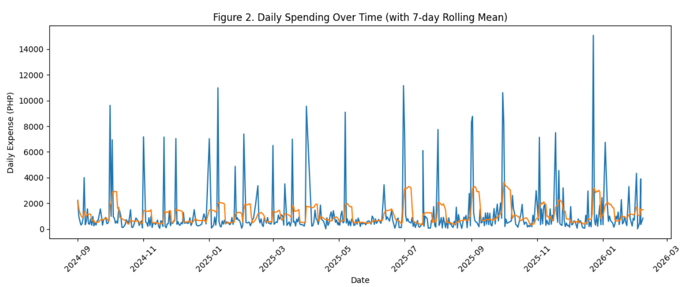

Fig. 2. Time Series of Daily Spending (September 2024 onward)

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.

E. Core Weekly Structure per Day Type

TABLE II
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

Table 2 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.

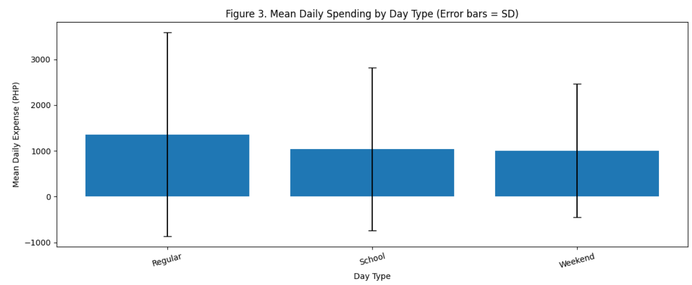

Fig. 3. Bar Chart of Mean Spending by Day_Type

Figure 3 shows that Regular days recorded the highest mean daily expense, while School and Weekend days clustered at lower and fairly similar averages. This after the large SD error bars, especially on Regular days, indicate substantial variability within each group and notable overlap across day types.

TABLE III
ONE-WAY ANOVA: DAILY_EXPENSE BY DAY_TYPE

Source	SS	df	MS	F	p-value
Between Groups	1.081193e+07	2	5405966.099839	1.564446	0.210287
Within Groups	1.631003e+09	472	3455515.669318		
Total	1.641815e+09	474			

Table 3 indicates that the one-way ANOVA did not detect a statistically significant difference in mean daily expense across day types ($F(2, 472) = 1.56$, $p = 0.210$). Consistent with this result, the between-groups variation ($SS = 1.08 \times 10^7$) was minimal relative to the substantial within-groups variation ($SS = 1.63 \times 10^9$), suggesting that day type accounts for only a small proportion of the overall variability in daily spending.

F. Category Behavior

TABLE IV
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

Category-level totals indicate that spending was concentrated in a small set of core necessities. Food accounted for the largest share of total expenses (PHP 149,173;

27.94%), followed by Personal (PHP 107,406; 20.12%) and Rent (PHP 101,834; 19.07%), together comprising approximately 67% of overall expenditure. School-related costs represented a notable secondary component (PHP 68,755; 12.88%), while Transportation (PHP 39,848; 7.46%) and Utilities (PHP 31,563; 5.91%) contributed moderate proportions. In contrast, Loan payments were relatively smaller (PHP 29,385; 5.50%), and Savings formed the smallest allocation (PHP 5,973; 1.12%), indicating that only a limited fraction of recorded outflows was directed toward formal saving within the observed period.

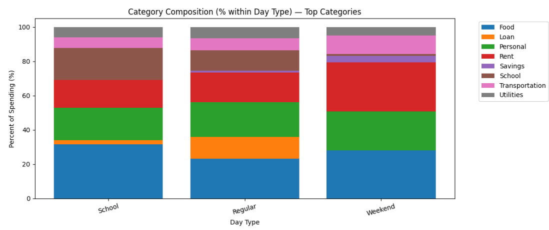

Fig. 4. Stacked Bar Chart of Category % by Day_Type

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.

G. Income Shock Analysis

Scholarship allowance receipts were treated as "shock dates." For each shock date, mean daily spending in the 3 days before and after the receipt was computed.

TABLE V
PAIRED T-TEST: DAILY EXPENSE BEFORE VS. AFTER SCHOLARSHIP RECEIPT

n	t	p	ΔM (After–Before)	Cohen's d	α
54	-0.6908	0.492683	-143.82	-0.0940	0.05

The paired-samples t-test comparing daily expenses before versus after scholarship receipt (Table X) indicated no statistically significant change in spending ($n = 54$, $t = -0.691$, $p = 0.493$ at $\alpha = 0.05$). Although the mean difference was negative (After–Before $= -$PHP 143.82), the associated effect size was negligible (Cohen's $d = -0.094$), suggesting that the observed decrease is small and consistent with routine variability rather than a meaningful shift attributable to scholarship receipt; therefore, the null hypothesis was retained.

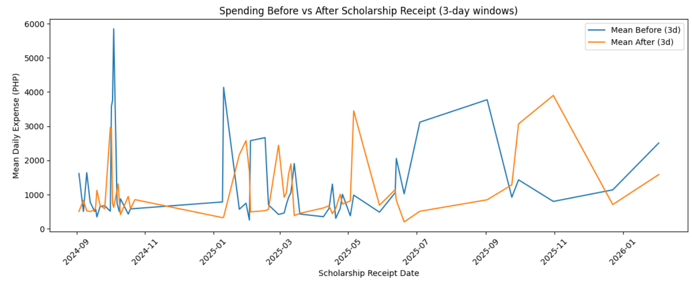

Fig. 5. Spending Before vs After Scholarship Receipt (3-day windows)

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.

H. Expense-Income Ratio

Fig. 6. Weekly Expense-Income Ratio Over Time

The weekly expense–income ratio in Figure X remained centered around 1.0 for most of the series, indicating that weekly expenses were generally comparable to weekly income. However, the pattern was intermittently disrupted by sharp spikes, most notably a peak above 4.0, reflecting weeks in which expenses substantially exceeded income, likely due to concentrated high-cost outflows and/or temporarily reduced inflows. Importantly, these exceedances were episodic rather than sustained, as the ratio repeatedly reverted toward the baseline range, suggesting that overspending relative to income occurred in short bursts rather than as a persistent trend over time.

The correlation heatmap (Figure X) indicates that linear relationships among the selected variables were generally weak. Daily expense exhibited only modest association with the income-context measures (scholarship receipt and time

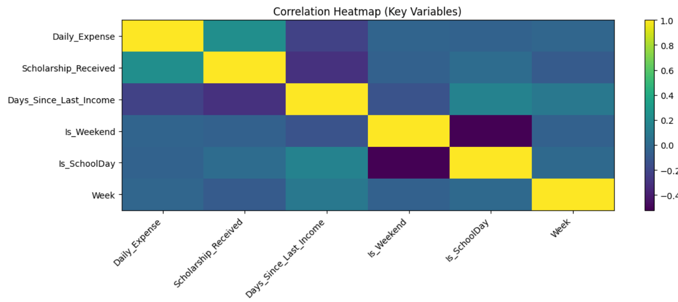

Fig. 7. Correlation Heatmap on Key Variables

since the most recent income entry), whereas the routine indicators (weekend and school-day status) showed little to no relationship with daily spending. Consistent with this pattern, the week index also suggested no meaningful monotonic trend in expenses over time. The most pronounced relationship in the matrix reflected the expected structural overlap between weekend and school-day indicators, while scholarship receipt aligned more closely with income timing rather than with day-type classifications.

I. Regression Model

TABLE VI
OLS Regression Predicting Daily Expense

Predictor	Coef.	SE	p
Intercept	1472.04	175.27	< 0.001
Is_Weekend	-366.59	233.16	0.117
Is_SchoolDay	-237.23	193.55	0.221
Scholarship_Received	1014.81	270.68	< 0.001
Days_Since_Last_Income	-214.00	59.06	< 0.001

$N = 475$, $R^2 = 0.084$, Adj. $R^2 = 0.076$, $F(4, 470) = 10.77$, $p = 2.32 \times 10^{-8}$.

An ordinary least squares (OLS) regression was fitted to evaluate whether routine-related indicators and income-context variables were associated with variation in daily expenses, specified as:

$$\begin{aligned} \textit{Daily\_Expense} &\sim \textit{Is\_Weekend} + \textit{Is\_SchoolDay} \\ &+ \textit{Scholarship\_Received} + \textit{Days\_Since\_Last\_Income} \end{aligned} \quad (1)$$

The model demonstrated modest explanatory power ($R^2 = 0.084$; Adj. $R^2 = 0.076$), indicating that the included predictors accounted for a small proportion of the observed variance in daily spending. Within this specification, *Scholarship_Received* emerged as a statistically significant positive predictor ($\beta = +$PHP 1,014.81; $p < 0.001$), suggesting higher daily expenses on days when a scholarship receipt was recorded, holding other variables constant. Conversely, *Days_Since_Last_Income* was a statistically significant negative predictor ($\beta = -$PHP 214.00 per day; $p < 0.001$), indicating that spending tended to decline as the time since the most recent income entry increased. In contrast, routine indicators were not statistically significant after accounting for income context (*Is_Weekend*: $p = 0.117$; *Is_SchoolDay*: $p = 0.221$), implying that day-type effects were not independently associated with daily expense within the model.

V. Discussion

A. Interpretation of Results

Although Regular days posted the highest mean daily expense and dispersion, the one-way ANOVA did not detect statistically significant mean differences across day types. In behavioral terms, this suggests that routine labeling alone was insufficient to explain day-level spending, because within-group variability (including spike days) overwhelmed average differences between groups. The large standard deviations and visible overlap support the idea that "what day it is" matters less than "what event happened on that day." This aligns with the broader self-tracking perspective that observable behavior is often shaped by episodic disruptions to routine rather than smooth, stable differences between calendar categories.

Meanwhile, category totals show that expenses were heavily concentrated in Food, Personal, and Rent, which together comprised roughly two-thirds of total outflows. This concentration indicates that the participant's spending behavior was anchored to necessities and recurring obligations rather than predominantly discretionary consumption. At the same time, the small recorded Savings allocation suggests that intentional saving, as captured by explicit "Savings" entries, remained limited relative to consumption and fixed costs—an outcome that may reflect the practical constraints of a student allowance budget, where discretionary capacity is bounded even with active tracking.

The paired t-test found no statistically significant change in mean spending before versus after scholarship receipt, indicating that post-receipt spending was not consistently higher or lower across events. The regression model found scholarship-receipt days to be associated with higher same-day expenses, and spending to decline as days since last income increased. Taken together, these findings suggest that scholarship receipt did not systematically shift spending across the entire post-receipt window, but it did coincide with higher spending on the receipt day itself and with a broader "tightening" pattern as time from income increased. This is consistent with temporal self-discipline and mental accounting perspectives: individuals often treat income arrival as a salient event that enables payments, catch-up purchases, or bill settlement, while also becoming more conservative as cash becomes temporally distant from the last replenishment. Importantly, the regression effect does not imply causality; it indicates an association that likely reflects the participant's tendency to schedule higher-cost obligations near income events.

The weekly expense–income ratio remained near 1.0 for much of the series but showed sharp episodic spikes. This pattern indicates that overspending relative to income occurred in short bursts rather than as a persistent state. Behaviorally, this supports the view that the participant's budget control was generally stable but periodically disrupted by clustered high-cost needs (e.g., rent, school fees, utilities, or other obligations). Such bursts can make "felt discipline" inconsistent: subjective perceptions may interpret spike weeks as loss of control even when the long-run balance remains near-neutral.

B. Comparison to Related Work

The results partially support prior literature on financial self-tracking and budgeting tools, but they also highlight where inferential testing adds nuance.

First, the observed concentration of spending in essential categories and the prevalence of low-spend days are consistent with research describing how expense trackers increase awareness of recurring patterns and cost drivers. The data structure—timestamps, categories, and descriptions—matches common expense-monitoring systems reported in prior work.

Second, the finding that day-type differences were not statistically significant contrasts with a common expectation that weekends reliably increase discretionary spending. However, the null ANOVA result is plausible in a student context where discretionary capacity is bounded and large fixed costs (e.g., rent) can occur on any day, masking calendar effects. This aligns with literature noting that many personal finance systems remain descriptive and do not formally test whether apparent differences are robust under variability. The present study's inferential results therefore extend the descriptive tradition by showing that visible mean differences may not survive statistical comparison when variance is high.

Third, the regression finding that spending declines as time since last income increases is consistent with temporal budgeting and mental accounting theory, in which people allocate resources across time windows and tighten spending as they perceive a budget period as "running out". Likewise, the same-day scholarship association suggests that income events may serve as triggers for scheduled obligations rather than immediate discretionary splurges—an interpretation compatible with research emphasizing routine-based self-discipline mechanisms in budgeting processes and the importance of temporal framing.

C. Limitations

This study 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 personal daily spending as a longitudinal behavioral dataset to determine whether statistically significant variations in mean expenses were associated with routine day types and short-term scholarship income events. Using a spreadsheet-based tracker and Python-based statistical analysis, the dataset captured 471 tracked days, 1,204 expense entries, and 312 income entries from September 1, 2024 to February 7, 2026, with total expenses of PHP 533,937.00 and total income of PHP 553,428.00.

Across the observation window, daily spending was characterized by a low baseline punctuated by infrequent high-cost spikes, producing a right-skewed distribution and substantial variance. Although Regular days showed the highest mean expense, inferential testing indicated that mean spending did not differ significantly across School, Regular, and Weekend day types, implying that episodic events and within-day-type variability dominated routine-label effects. Category analysis showed that expenditures were concentrated in Food, Personal, and Rent, indicating that the participant's spending behavior was anchored to necessities and recurring obligations. Scholarship receipt did not produce a statistically detectable average pre–post shift, but regression results suggested that spending tended to be higher on scholarship-receipt days and decreased as time since the last income increased, consistent with temporally structured budgeting behavior.

From a behavioral 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. 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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