Analyzing Temporal and Categorical Patterns in Personal Spending Behavior

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Abstract— This study analyzes temporal and categorical patterns in personal spending behavior using four months of self-tracked expense data. The research examines differences between needs-based and wants-based expenses, compares spending behavior across weekdays and weekends, and identifies expense categories that contribute most to total spending and variability. Descriptive statistics, data visualizations, non-parametric and parametric statistical tests, and correlation analysis were applied to explore spending patterns. The results indicate no statistically significant differences between needs and want or between weekday and weekend spending, while category-level analysis revealed uneven contributions and variability across expense types. These findings demonstrate that individual-level expense tracking can provide meaningful insights into personal financial behavior and support improved financial awareness and decision-making.

***Index Terms*— Personal expense tracking, temporal analysis, categorical analysis, needs versus wants, weekday versus weekend spending, descriptive statistics, correlation analysis, data visualization.**

I. Introduction

Personal financial behavior is a critical aspect of daily life that reflects an individual's priorities, needs, and decision-making processes [1]. Through the availability of digital tools, individuals now have the ability to monitor their personal finances down to the last detail [2]. This research study was conducted over the course of four months to look at personal expenditure behaviors by looking at differences in expenditure types (needs versus wants), day of week, and to account for the total spending based on expenditure type [3].

Understanding how an individual spends their money is important, as an individual's financial habits create their own budgets and savings plans and ultimately affect their financial future [4]. Being unaware of the way in which you spend your money can result in overspending and/or poorly distributing your money. By reviewing personal finance expense data individuals can better manage their finances and make educated and responsible financial choices [5]. Previous studies on monitoring personal data suggested that using statistical and temporal methods, tracking personal behaviors like sleep, productivity, and activity would yield statistical data regarding how personal behaviors impact each individual and their overall health. Similarly, research on personal finances has shown that individuals can better understand how they spend their money, make discretionary purchases, and fulfill their obligations by categorizing their expenses over time.

Despite these findings, most studies rely on aggregated or population-level datasets, which may overlook individual behavioral differences. There is limited research on personal expense tracking that considers both temporal factors (weekdays versus weekends) and categorical distinctions (needs versus wants). This study addresses this gap by exploring individual-level expense data to identify meaningful temporal and categorical spending patterns, specifically analyzing how spending differs between needs and wants, varies across weekdays and weekends, and which categories contribute most to total spending and its variability.

Based on these objectives, the study seeks to answer the following research questions:

1. How do statistical spending patterns differ between needs-based and wants-based expenses?
2. What temporal patterns can be identified in spending behavior when comparing weekdays and weekends?
3. Which expense categories show the highest contribution and variability in total spending?

II. Literature Review

Previous studies on personal and behavioral data have examined a wide range of daily activities, such as sleep behaviors, mood changes, gaming habits, physical activities, productivity levels [6]. The main objective was to identify how personal behavior patterns develop over time and how these patterns impact an individual's overall well-being and performance. Researchers who focused on measurable daily behaviors were able to demonstrate that, though a person's behavior might change from week to week, month to month or year to year, it consistently demonstrates temporal patterns like the difference between weekdays and weekends). These findings support the idea that personal data, even at the individual level, can reveal meaningful behavioral trends.

In terms of methodology, prior research commonly relied on self-tracked or digitally recorded data collected through mobile applications, wearable devices, or manual logs [7]. Many visualization techniques were used to illustrate trends and comparisons over time and across categories such as histograms, line graphs, bar charts, etc. All these techniques helped researchers capture temporal (time) and categorical (e.g. between weekday/weekend) variations in an individual's behavior. These approaches allowed researchers to capture both temporal and categorical variations in personal behavior.

The main findings from these studies provide evidence that individual behavior is influenced by both time and context factors [8]. Among other things, researchers found that average sleep and productivity differed from weekday to weekend, while also noting that an individual's level of activity would fluctuate based on daily routines. In studies focused specifically on personal finances, tracking spending by category over time allowed researchers to determine how individuals are spending money in relation to both discretionary and essential needs. However, several studies suffered from common weaknesses, such as reliance upon aggregate datasets, short duration of data collection, and limited scope in the analysis of individual behaviors, demonstrating the limitation of studies in capturing nuanced individual behaviors.

This project is similar to the previous research using self-tracking, time of spending analysis, and statistical techniques to measure spending behavior. However, the focus of this study is specifically on tracking spending based on time (weekday vs. weekend) and category (need vs. want) for an individual [9]. By analyzing four months of personal financial data, this study addresses gaps in existing literature by providing a detailed, individual-centered examination of spending behavior, contributing additional insight into how personal financial habits evolve over time.

III. METHODOLOGY

This study employed a quantitative, single-subject design to examine personal financial behavior over a four-month period. The methodology focuses on collecting, cleaning, and analyzing daily expense data to identify temporal and categorical spending patterns. This section describes the participants, data collection procedures, operational definitions of variables, data cleaning steps, and statistical analyses used to answer the research questions. The goal is to provide sufficient detail so that the study can be replicated by other researchers.

A. *Participants*

The participant in this study was a college student aged 20–25. The student is currently enrolled in the Bachelor of Science in Computer Science program at National University. This study followed a single-subject design to track personal financial behavior over a four-month period.

B. *Data Collection Methods*

Variables collected:

- Date of Expense
- Expense Category (Food, Transportation, Entertainment)
- Amount
- Day Category (Weekday or Weekend)

Frequency of Data Logging: Daily

Tools Used: iPhone Notes Application

Data Collection Period: 4 Consecutive Months

C. *Operational Definitions*

1) Any monetary transaction recorded during the data collection period:

Expense Type:

- Need: Essential expenses (e.g., food, transportation, school-related costs)
- Want: Non-essential or discretionary expenses

2) Specific classification of spending (e.g., food, transportation, entertainment)

   Day Category:

   - Weekday: Monday to Friday
   - Weekend: Saturday and Sunday

3) Monetary value of each expense, standardized to a consistent currency unit

   - Amount

D. *Data Cleaning*

Prior to analysis, the dataset was cleaned to ensure accuracy and consistency. Missing values were identified and addressed, and text-based entries were converted into numerical formats where necessary. Expense categories and expense types were standardized to remove inconsistencies in labeling. Dates were formatted uniformly to allow proper temporal analysis, and all monetary values were checked to ensure consistent units of measurement. No extreme outliers were removed, as all recorded expenses reflected real transactions.

E. *Statistical Analysis*

The cleaned dataset was analyzed using descriptive and inferential statistical methods. Descriptive statistics, including mean, median, and standard deviation, were computed to summarize overall spending behavior. Non-parametric statistical tests were applied to compare spending between needs and wants, as well as between weekdays and weekends, due to unequal sample sizes and non-normal distributions. Correlation analysis was conducted to examine relationships between expense categories and total spending. Data visualizations such as bar charts, histograms, time-series plots, and correlation matrices were used to clearly present patterns and trends in the data. Potential sources of bias, including self-reporting and single-subject design, were considered when interpreting the results.

IV. RESULTS

4.1 Overview of the Dataset

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df.head()
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	Date	Expense_Category	Amount	Expense_Type	Day_Category
4	2025-05-06	Transportation	53	Need	Weekday
5	2025-05-06	Food	45	Need	Weekday
6	2025-05-06	Haircut	255	Need	Weekday
9	2025-08-06	Transportation	108	Need	Weekend
10	2025-08-06	Grocery	578	Need	Weekend

Figure 1. Cleaned Personal Expense Dataset

Figure 1 shows a sample of the cleaned dataset used in the analysis, including the date of transaction, expense category, expense type, amount spent, and day classification.

4.2 Research Question 1: Needs-Based vs Wants-Based Expenses

4.2.1 Descriptive Analysis of Expense Types

Expense_Type	count	mean	median	std	min	max	sum
Need	112	150.928571	105.0	138.272854	10	603	16904
Want	13	208.923077	89.0	285.612634	39	928	2716

Table 1 presents the descriptive statistics of expenses categorized as needs and wants. The table summarizes the number of recorded transactions, central tendency, and variability of spending amounts for each expense type over the four-month period.

4.2.2 Distribution of Spending Amounts by Expense Type

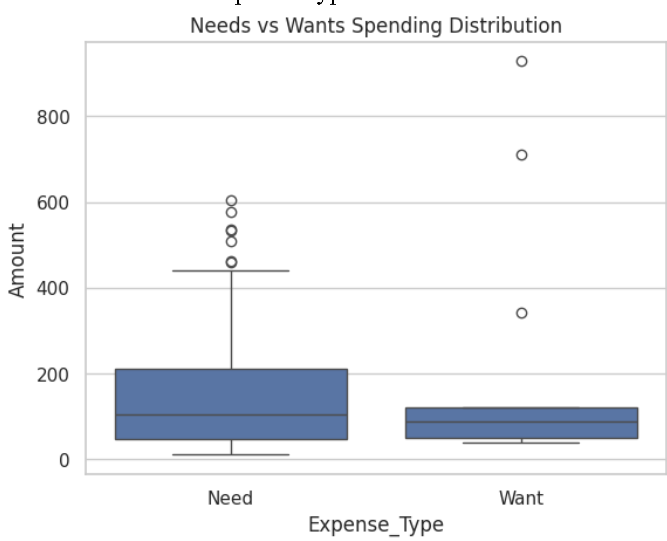


Figure 2. Needs vs Wants Spending Distribution

Figure 2 shows the distribution of spending amounts for needs-based and wants-based expenses. The visualization displays differences in the range and dispersion of expense values between the two categories.

4.2.3 Statistical Test Results

Mann–Whitney U test

$U = 735.5$

$p = 0.9548$

A Mann–Whitney U test was conducted to assess whether there was a statistically significant difference between needs-based and wants-based expenses. The results indicate that the difference in spending amounts between the two categories was not statistically significant ($U = 735.5$, $p = 0.9548$).

4.3 Research Question 2: Weekday vs Weekend Spending Patterns

4.3.1 Descriptive Analysis of Spending by Day Category

Day_Category	mean	median	std	sum
Weekday	147.436782	99.0	155.854039	12827
Weekend	178.763158	113.5	166.472696	6793

Table 2. Descriptive statistics of weekday and weekend spending

Table 2 summarizes the descriptive statistics of spending amounts based on day category. The table presents the mean, median, standard deviation, and total spending for expenses recorded on weekdays and weekends over the four-month period.

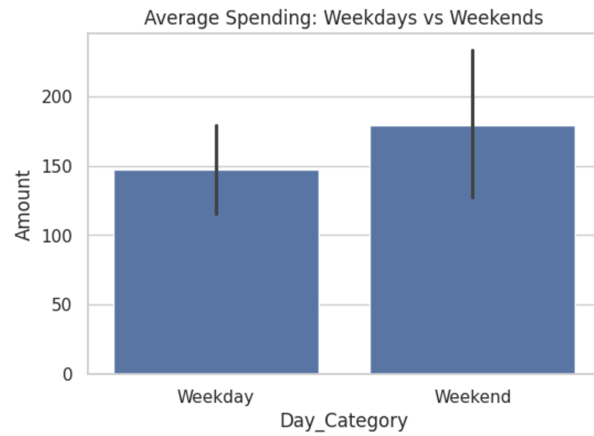


Figure 3. Average Spending: Weekday vs Weekends

Figure 3 illustrates the difference in average spending between weekdays and weekends. The visualization highlights variation in mean expense amounts across the two-day categories.

4.3.3 Statistical Test Results

Independent samples t-test

$t = -0.9864$

$p = 0.3275$

An independent samples t-test was conducted to examine differences in spending between weekdays and weekends. The results indicate that the difference in average spending between the two-day categories was not statistically significant ($t = -0.99$, $p = 0.33$).

4.4 Research Question 3: Expense Category Contribution and Variability

4.4.1 Contribution of Expense Categories to Total Spending

Expense_Category	sum	mean	std
Food	10673	187.245614	140.186773
Transportation	4123	93.704545	89.207774
Staycation	1270	635.000000	414.364574
Grocery	1181	590.500000	17.677670
Ticket	712	712.000000	NaN
Haircut	605	201.666667	52.519838
Load	277	55.400000	29.228411
Shopee Order	214	71.333333	28.041636
Computer Shop	200	50.000000	0.000000
Tiktok Order	120	120.000000	NaN
Billiards	100	100.000000	NaN
Flower	100	100.000000	NaN
Print	45	45.000000	NaN

Table 3. Summary statistics of spending by expense category

Table 3 presents the summary statistics of spending aggregated by expense category. The table reports the total spending, average amount, and variability of expenses for each category recorded during the four-month period.

4.4.2 Total Spending by Expense Category

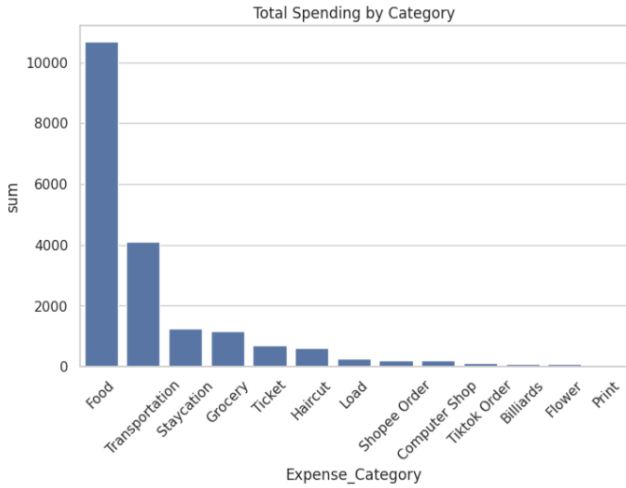
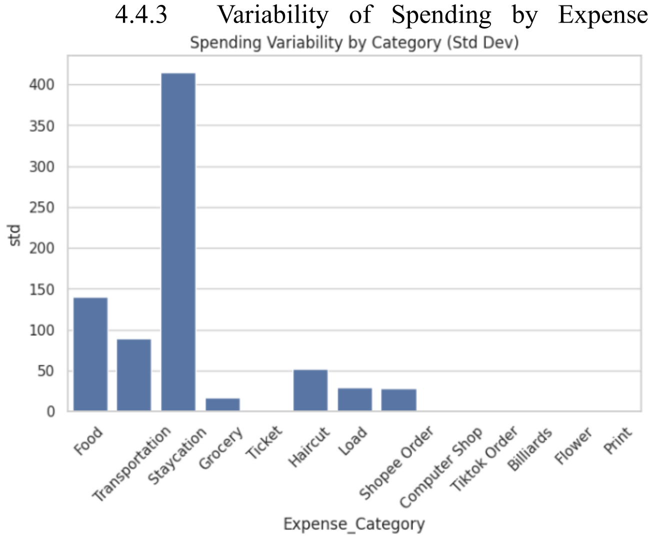


Figure 4. Total Spending by Expense Category

Figure 4 illustrates the distribution of total spending across expense categories. The visualization highlights differences in overall contribution among categories based on aggregated expense amounts.

4.4.3 Variability of Spending by Expense



Category

Figure 5. Spending Variability by Expense Category (Standard Deviation)

Figure 5 presents the variability of spending amounts across expense categories. The standard deviation values indicate differences in the dispersion of expenses within each category.

4.5 Correlation Analysis of Expense Categories

4.5.1 Correlation Matrix

Expense_Category	Billiards	Computer Shop	Flower	Food	Grocery	Haircut	Load	Print	Shopee Order	Staycation	Ticket	Tiktok Order	Transportation
Expense_Category													
Billiards	1.000000	-0.030542	-0.014925	-0.031201	-0.021262	-0.025647	-0.030903	-0.014925	-0.024937	-0.019259	-0.014925	-0.014925	0.093739
Computer Shop	-0.030542	1.000000	-0.030542	0.025128	-0.043509	-0.052482	-0.063239	-0.030542	-0.051029	-0.039411	-0.030542	-0.030542	-0.059996
Flower	-0.014925	-0.030542	1.000000	0.054916	-0.021262	-0.025647	-0.030903	-0.014925	-0.024937	-0.019259	-0.014925	-0.014925	0.117040
Food	-0.031201	0.025128	0.054916	1.000000	0.082041	0.078573	-0.142707	-0.085236	-0.159705	-0.093250	0.081933	-0.132516	0.112280
Grocery	-0.021262	-0.043509	-0.021262	0.082041	1.000000	-0.036535	-0.044024	-0.021262	-0.035524	0.639757	-0.021262	-0.021262	-0.016131
Haircut	-0.025647	-0.052482	-0.025647	0.078573	-0.036535	1.000000	-0.053102	-0.025647	-0.042849	-0.033094	-0.025647	-0.025647	0.021229
Load	-0.030903	-0.063239	-0.030903	-0.142707	-0.044024	-0.053102	1.000000	0.416692	-0.051632	-0.039877	-0.030903	-0.030903	-0.084376
Print	-0.014925	-0.030542	-0.014925	-0.085236	-0.021262	-0.025647	0.416692	1.000000	-0.024937	-0.019259	-0.014925	-0.014925	-0.032960
Shopee Order	-0.024937	-0.051029	-0.024937	-0.159705	-0.035524	-0.042849	-0.051632	-0.024937	1.000000	-0.032178	-0.024937	-0.024937	-0.147527
Staycation	-0.019259	-0.039411	-0.019259	-0.093250	0.639757	-0.033094	-0.039877	-0.019259	-0.032178	1.000000	-0.019259	-0.019259	0.034359
Ticket	-0.014925	-0.030542	-0.014925	0.081933	-0.021262	-0.025647	-0.030903	-0.014925	-0.024937	-0.019259	1.000000	-0.014925	0.067525
Tiktok Order	-0.014925	-0.030542	-0.014925	-0.132516	-0.021262	-0.025647	-0.030903	-0.014925	-0.024937	-0.019259	-0.014925	1.000000	-0.088299
Transportation	0.093739	-0.059996	0.117040	0.112280	-0.016131	0.021229	-0.084376	-0.032960	-0.147527	0.034359	0.067525	-0.088299	1.000000

Table 4. Correlation matrix of expense categories

Table 4 presents the correlation coefficients between expense categories based on aggregated daily spending. The values indicate the strength and direction of linear relationships between categories across the data collection period.

4.5.2 Heatmap Visualization of Category Correlations

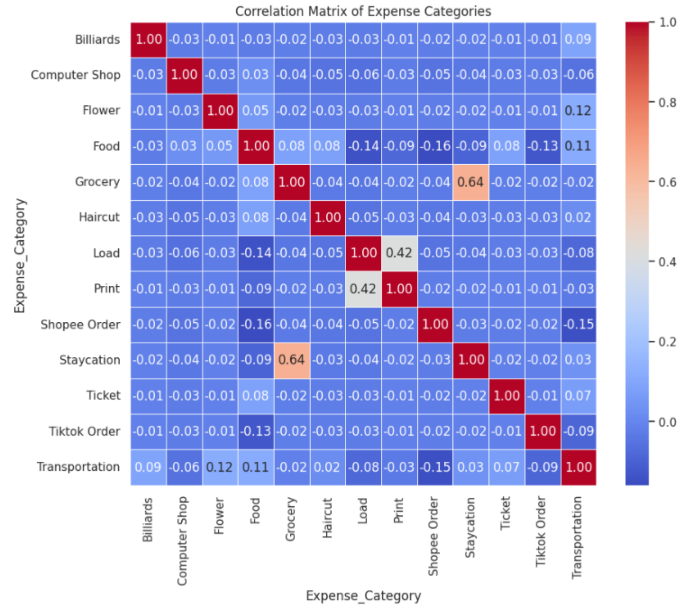


Figure 7. Heatmap of Expense Category Correlations

Figure 7 visually represents the correlation matrix shown in Table 4. The heatmap allows for easier comparison of correlation strengths across expense categories by using color-coded values.

V. Discussion

A. Interpretation of Results

This research offers insight into how people spend money, both over time and across Temporal and Categorical dimensions. The researchers determined that there are no statistical differences between needs-based and wants-based expenses, despite observable differences in their distributions. This suggests that while needs occurred more frequently, the monetary value of individual transactions did not differ substantially between the two categories. This pattern may reflect discretionary purchases occasionally reaching amounts comparable to essential expenses.

Similarly, the comparison between weekday and weekend spending revealed no statistically significant difference in average expenditure. Although weekend spending appeared slightly higher in descriptive statistics, the statistical test indicated that spending behavior remained relatively consistent across the week. This consistency may be explained by routine daily expenses, such as food and transportation, occurring regardless of day type.

An expense category analysis determined that expense categories are driving a considerable portion of total spending while other expense categories are much less variable in terms of the amount of money spent. Expense categories that are very variable in terms of the amount spent represent sporadic or non-routine purchases; expense categories that are less variable represent relatively stable, frequent expenditures. The correlation analysis suggested little or no relationship between each of the categories. As a result, spending in one category may not help to predict spending in another category.

B. Comparison to Related Work

The results of this analysis support the findings from previous studies on tracking individual and behavioral data, which indicate that individuals' behaviors may have stable patterns over time and are also very similar across temporal categories (for example, weekdays vs. weekends). Previous research using self-tracking data has demonstrated that expense categorization provides insight into financial behaviors; however, categorizing expenses does not always result in a statistically significant difference between behavioral groups.

In personal finance research, earlier studies have emphasized the usefulness of expense categorization in understanding discretionary and essential spending. The lack of strong relationships among categories in this study further supports previous literature stating that an individual's financial behavior is context dependent, not strongly correlated across categories. However, unlike analysis of populations in which studies typically find more representative trends, the analysis of this sample has revealed that personal financial behavior is often subtle and highly variable.

C. Limitations

This study has several limitations that should be considered when interpreting the results. First, the dataset represents a single participant (n = 1), which limits the generalizability of the findings. Second, the data relied on self-reported expense tracking, which may introduce reporting inaccuracies or omissions. Third, some expense categories contained relatively few observations, reducing the reliability of statistical comparisons. Finally, the four-month data collection period may not fully capture long-term or seasonal spending patterns.

D. Recommendations and Future Work

Future studies could expand on the current research results by involving more than one person to facilitate a comparison of groups. Using dedicated expense-tracking applications with automated logging could reduce self-report bias and improve data accuracy. Extending the time frame in which data is collected to longer than four months would also enable researchers to explore longer-term trends and the effect of seasons on consumer spending. Additionally, future studies could also incorporate other variables such as income level, budgeting goals, and indicators of financial stress to gain a more complete understanding of how individuals conduct their personal finances.

VI. Conclusion

This study examined how an individual spends their money temporally and categorically through four months of self-reported expense records. Comparisons were made between weekday and weekend spending to determine which expense categories contributed most to total spending and variability by looking at how much of each spend falls in the needs category versus want category. While the research findings do not indicate statistically significant differences between needs and wants or between weekday versus weekend spending, many expense categories contributed a larger percentage to total spend versus others with more variable amounts.

Analyzing personal expense data increased awareness of individual financial habits and spending patterns. The results emphasized how frequently routine expenses occurred and how irregular purchases contributed to variability in overall spending. This study provides evidence of the benefits of ongoing expense tracking to better understand one's own financial behavior and identifying areas that may require closer monitoring.

The findings of this study individuals can use these to regularly keep track of their spending and review their expenses to help them create a budget and plan their finances better. If individuals know how much they spent during the year and on what categories, they will be able to make informed financial decisions. Overall, the findings of this study suggest that for individual-level personal expense tracking can be a valuable tool for understanding financial behavior as a way and method of improving financial management.

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