Analysis of Personal Spending Behavior Through GCash Expense Transactions

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***Abstract*—The increasing adoption of digital wallets has transformed personal financial management by enabling fast, cashless transactions and real-time expense monitoring. However, the convenience of electronic payments may reduce spending awareness and influence financial behavior. This study analyzes one year of personal GCash expense transactions to examine spending patterns, category distribution, and temporal trends in digital wallet usage. Exploratory data analysis and statistical techniques were applied to categorize expenses, evaluate transaction frequency, and identify monthly spending variations. Descriptive results indicate that most transactions were small to medium in value, while high-value payments, particularly school fees and large transfers, accounted for the largest share of total expenses. Time-series analysis revealed fluctuations in monthly spending, with peak expenditures associated with major financial obligations. Statistical testing showed no significant difference between weekday and weekend spending, whereas analysis of variance confirmed significant differences in expense amounts across categories. The findings highlight the value of analyzing personal transaction data to improve financial awareness, support budgeting decisions, and promote responsible spending behavior in an increasingly cashless economy.**

***Index Terms*—Digital wallet, personal finance analytics, spending behavior, exploratory data analysis, transaction data, financial awareness**

I. Introduction

The rapid advancement of digital financial technologies has transformed the way individuals manage and spend money. Mobile wallets and electronic payment platforms enable users to perform transactions quickly, monitor balances in real time, and conduct cashless payments across a wide range of services. In the Philippines, digital wallet platforms such as GCash have gained widespread adoption due to their convenience, accessibility, and integration into everyday transactions including bills payment, online shopping, money transfers, and food delivery services.

Despite the convenience provided by digital wallets, the ease of cashless transactions may reduce users' awareness of their spending behavior. Research suggests that electronic payment methods can influence spending patterns by reducing the psychological "pain of paying," making transactions feel less tangible than cash payments [1], [2]. As a result, individuals may be more likely to increase discretionary spending or lose track of their expenses over time [3]. Understanding personal spending behavior through transaction records is therefore important for improving financial awareness and decision-making.

Previous research has explored financial behavior, consumer spending habits, and digital payment adoption. Digital wallet usage has been linked to improved convenience and financial inclusion, particularly in developing economies [4]. However, the frictionless nature of digital payments can also encourage increased spending frequency and impulsive purchases [5]. Studies in financial literacy emphasize that awareness and monitoring of expenses play a crucial role in maintaining financial stability [6]. While large-scale studies provide valuable insights into consumer trends, fewer studies focus on personal-level transaction analysis as a tool for self-awareness and behavioral improvement.

Personal data analytics has emerged as an effective approach for understanding individual habits and decision-making patterns. Analyzing personal financial records allows individuals to identify spending patterns, recognize unnecessary expenses, and develop improved financial management strategies [7]. With the availability of digital wallet transaction logs, individuals can apply data analysis techniques to uncover patterns in their own financial behavior.

This study aims to explore personal expense behavior using one year of GCash transaction data. By applying exploratory data analysis techniques, the research identifies spending distribution across categories, transaction frequency patterns, and temporal trends in expenses. Understanding these patterns can provide insights into personal financial habits and support improved budgeting and spending decisions.

A. General Objective

The general objective of this study is to analyze personal expense transactions recorded in GCash over a one-year period to identify spending patterns, behavioral trends, and statistical differences in spending behavior.

B. Specific Objectives

To achieve the general objective, this study seeks to:

- Categorize expense transactions into meaningful spending groups.
- Identify spending categories with the highest total expenditure.

- Measure the frequency of expense transactions per category.
- Analyze monthly trends in personal expenses.
- Summarize overall expense behavior using descriptive statistics.
- Examine differences and relationships in spending behavior using statistical analysis.

C. Research Questions

Aligned with the objectives, the study addresses the following research questions:

- **RQ1:** Which categories account for the highest personal expenses?
- **RQ2:** How frequently do expense transactions occur within each category?
- **RQ3:** How do personal expenses change over time?
- **RQ4:** What patterns can be observed in overall spending behavior?
- **RQ5:** Are there significant differences or relationships in spending behavior across categories and time periods?

II. Review of Related Literature

A. Digital Wallet Adoption and Financial Behavior

The adoption of digital wallets has increased significantly worldwide due to their convenience and efficiency in facilitating financial transactions. Digital payment systems reduce reliance on physical cash and enable seamless financial interactions across sectors such as retail, utilities, and transportation [8]. In developing economies, mobile wallet platforms have improved financial inclusion by providing access to financial services for previously unbanked populations [4].

Research indicates that the convenience of digital payments can influence consumer spending behavior. Electronic payment systems reduce the psychological burden associated with spending, making transactions feel less tangible and potentially increasing consumer expenditures [1]. This abstraction effect can influence financial decision-making and spending awareness [2].

B. Impact of Cashless Payments on Spending Patterns

Studies have shown that consumers tend to spend more when using cashless payment methods compared to traditional cash transactions [3]. The frictionless nature of digital payments allows users to complete transactions quickly, potentially encouraging impulsive purchases and higher transaction frequency [5]. In addition, promotional incentives and integrated payment features may further influence spending habits [9].

Behavioral economics research suggests that payment methods can shape financial decision-making processes. Consumers using electronic payments may underestimate their total expenditures and engage more frequently in discretionary spending [10]. Consequently, monitoring transaction data becomes essential for improving spending awareness and financial discipline.

C. Personal Financial Management and Spending Awareness

Financial literacy and expense awareness are essential for maintaining financial stability. Monitoring expenses allows individuals to identify unnecessary expenditures and implement more effective budgeting strategies [6]. Financial education and expense tracking tools have been shown to improve financial capability and encourage responsible spending habits [11].

Analyzing personal transaction records enables individuals to evaluate their spending behavior and recognize patterns that may not be evident without systematic analysis [7]. Such insights can support behavioral adjustments, including reducing non-essential expenses and prioritizing essential spending.

D. Data Analytics in Personal Behavioral Studies

Data analytics techniques are widely used to analyze behavioral patterns and support decision-making. Exploratory data analysis (EDA) allows researchers to summarize datasets, detect patterns, and identify anomalies [12]. Visualization techniques enhance understanding by presenting complex data in accessible graphical formats [13].

Time-series analysis is useful for examining behavioral trends over time, allowing researchers to observe periodic fluctuations and spending cycles [14]. Applying these analytical techniques to personal financial data can reveal spending patterns, peak expense periods, and behavioral trends associated with lifestyle factors.

E. Research Gap

While numerous studies have explored digital payment adoption and consumer spending behavior, most focus on large populations or survey-based data. Limited research has examined personal-level digital wallet transaction logs as a means of understanding individual financial behavior. This study addresses this gap by applying exploratory data analysis techniques to personal expense data, providing insights into individual spending habits and financial behavior patterns.

III. Methodology

This chapter describes the procedures and analytical methods used to examine personal expense behavior using GCash transaction records. It details the data source, preprocessing procedures, variable definitions, and statistical techniques used to analyze spending patterns.

A. Participants

The participant in this study is the researcher (n = 1), a college student who regularly uses GCash as a primary digital wallet for daily financial transactions. No personally identifiable information is disclosed. The study focuses exclusively on personal expense behavior derived from transaction records.

B. Data Collection Methods

The dataset consists of one year of personal GCash transaction records exported from the GCash mobile application. The transactions represent routine financial activities such as online purchases, digital subscriptions, mobile load purchases, transfers, and educational payments.

After exporting the transaction records, the description field was manually reviewed to protect privacy and ensure ethical handling of sensitive information. Mobile numbers appearing in transaction descriptions were anonymized prior to analysis. The researcher's personal number was replaced with the label "My_Number", while other numbers were replaced with "Others_Number". This step prevented the disclosure of personally identifiable information while preserving the analytical value of the dataset.

TABLE I
DATASET VARIABLES AND DESCRIPTIONS

Variable	Description	Type
Date and Time	Timestamp when the transaction occurred	Datetime
Description	Text describing the transaction details	Categorical (Text)
Transaction ID	Unique identifier for each transaction	Categorical (Identifier)
Debit	Amount deducted from the account (expense)	Numeric (Continuous)
Credit	Amount added to the account (income)	Numeric (Continuous)
Balance	Account balance after the transaction	Numeric (Continuous)

This study focuses solely on expense transactions, defined as records with positive debit values.

C. Operational Definitions of Variables

Additional variables were derived to support behavioral and temporal analysis.

- Year and Month – used to analyze spending trends over time
- Day of Week – used to evaluate weekly spending behavior
- Weekend Indicator – identifies whether a transaction occurred on a weekend

D. Data Cleaning and Preprocessing

Data cleaning and preprocessing were conducted using Python and the Pandas library to ensure accuracy and consistency.

The following procedures were performed:

1) Converted the date column into datetime format.
2) Converted debit values to numeric format.
3) Replaced missing values with zero.
4) Removed duplicate records.
5) Sorted transactions chronologically.
6) Filtered the dataset to retain only expense transactions.

These steps ensured data accuracy, consistency, and reliability for analysis.

E. Expense Categorization Procedure

Table II shows the expense transactions that were categorized using keyword-based classification applied to the description field. Keywords representing merchants, services, or transaction types were identified and mapped to predefined spending categories.

TABLE II
KEYWORD-BASED EXPENSE CATEGORIZATION

Category	Representative Keywords
apple_services_payment	apple services
spotify_subscription_payment	spotify
online_shopping_payment	shopee, lazada, tiktok
food_delivery_payment	grab, foodpanda
game_payment	mlbb, steam, genshin, xsolla, honkai
buy_load	load, gigalife
bdo_to_gcash_transfer	bdo
outgoing_transfer	from [mobile number]
incoming_transfer	to [mobile number], starting balance
school_fee_payment	National University, Bancnet P2M

The classification process used case-insensitive keyword matching. When multiple keywords were present, the transaction was assigned to the most relevant category.Examples of keyword mappings include digital subscription services, online shopping platforms, gaming services, telecommunications providers, and transfer identifiers.

Transactions that did not match predefined keywords were manually reviewed and assigned to the most appropriate category.

F. Exploratory Data Analysis

Exploratory data analysis (EDA) was conducted to summarize spending patterns and identify behavioral trends.

1) Descriptive Statistics: The following descriptive measures were computed:

- Total expenses
- Average expense per transaction
- Mean, median, and standard deviation
- Highest expense transactions

2) Category Analysis:

- Total spending per category
- Transaction frequency per category
- Percentage distribution of expenses

3) Time-Series Analysis:

- Monthly expense totals
- Monthly transaction frequency
- Identification of peak spending periods

4) Distribution Analysis: Expense amounts were analyzed to determine spending patterns and detect skewness in the distribution.

G. Statistical Analysis

Statistical tests were conducted to evaluate spending behavior patterns.

1) Independent Samples t-Test: An independent samples t-test was conducted to determine whether a significant difference exists between weekday and weekend spending.

Null Hypothesis (H0): There is no significant difference between weekday and weekend expense amounts.

Alternative Hypothesis (H1): There is a significant difference between weekday and weekend expense amounts.

The t-statistic is computed as:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{1}$$

where:

- $\bar{X}_1$, $\bar{X}_2$ = mean expenses for weekdays and weekends
- s_1^2, s_2^2 = variances of the two groups
- n_1, n_2 = sample sizes of the two groups

2) Analysis of Variance (ANOVA): A one-way analysis of variance (ANOVA) was performed to determine whether significant differences exist in expense amounts across spending categories.

Null Hypothesis (H0): There is no significant difference in mean expense amounts across spending categories.

Alternative Hypothesis (H1): At least one spending category has a significantly different mean expense amount.

The ANOVA F-statistic is computed as:

$$F = \frac{\text{Between-group variance}}{\text{Within-group variance}} \tag{2}$$

More formally,

$$F = \frac{SS_{between}/df_{between}}{SS_{within}/df_{within}} \tag{3}$$

where:

- $SS_{between}$ = sum of squares between groups
- SS_{within} = sum of squares within groups
- df = degrees of freedom

3) Correlation Analysis: Correlation analysis was conducted to examine the relationships among expense amounts, spending categories, and selected time-based variables. Pearson's product-moment correlation coefficient (r) was used to measure the strength and direction of linear relationships between continuous variables.

For categorical spending groups, binary indicator (dummy) variables were created to allow correlation analysis with expense amounts. This enabled the assessment of whether particular categories were associated with higher or lower expense values.

The hypotheses tested for each correlation were:

- **H0:** There is no significant linear relationship between the variables ($\rho = 0$).
- **H1:** There is a significant linear relationship between the variables ($\rho \neq 0$).

Correlation coefficients range from -1 to +1, where values closer to ±1 indicate stronger relationships and values near 0 indicate weak or no linear relationship. Statistical significance was evaluated at the 0.05 level.

The analysis was used to determine whether higher transaction frequency, specific spending categories, or time-related variables were associated with increased expense amounts.

H. Data Visualization

Data visualizations were created using Matplotlib and Seaborn to support interpretation of results, including:

- Bar charts for category spending
- Line graphs for monthly trends
- Histograms for expense distribution
- Pie charts for category distribution
- Boxplots for category comparisons
- Heatmaps for correlation analysis

I. Ethical Considerations

This study uses only personal financial data belonging to the researcher. No sensitive personal identifiers are disclosed. The analysis is conducted solely for academic purposes and to improve understanding of personal spending behavior.

IV. Results

This section presents the findings derived from the exploratory analysis of personal GCash expense transactions collected over a one-year period. The results include descriptive statistics, category-based spending distribution, temporal trends, and statistical analyses.

A. Dataset Overview

A total of 174 expense transactions were recorded during the study period. The dataset spans from February 2, 2025 to February 2, 2026, representing one full year of personal digital wallet spending activity.

B. Annual Expenses Summary

The total expense recorded during the one-year study period amounted to PHP 161,115.06. This represents the overall amount spent using the GCash digital wallet during the study period.

TABLE III
Total Expenses by Category

Category	Total Amount (PHP)
school_fee_payment	70,152.00
outgoing_transfer	55,857.00
game_payment	12,030.79
online_shopping_payment	7,587.02
apple_services_payment	7,532.00
buy_load	3,519.00
food_delivery_payment	3,413.25
spotify_subscription_payment	1,024.00

As shown in Table III, school fee payments accounted for the highest total expenses, amounting to PHP 70,152.00, followed by outgoing transfers totaling PHP 55,857.00. Although game-related payments were the most frequent transactions, they contributed significantly less to overall spending compared to high-value obligations such as school fees and transfers.

These values correspond to the percentage distribution shown in Figure 2.

TABLE IV
DESCRIPTIVE STATISTICS OF EXPENSE AMOUNTS

Statistic	Value (PHP)
Number of Transactions	174
Minimum Expense	10.64
Maximum Expense	26,523.60
Mean Expense	925.95
Median Expense	161.24
Standard Deviation	3,157.34

C. Descriptive Statistics of Expense Transactions

Descriptive statistics were computed to summarize the overall characteristics of expense transactions. As shown in Table IV, the minimum expense recorded was PHP 10.64, while the maximum expense reached PHP 26,523.60.

The mean expense amount was PHP 925.95, whereas the median expense was significantly lower at PHP 161.24. This difference indicates a right-skewed distribution, where a small number of high-value transactions increased the overall average.

The standard deviation of PHP 3,157.34 further suggests substantial variability in expense amounts. Most transactions consisted of low-value expenses, while a few high-value payments contributed disproportionately to total spending.

D. Expense Distribution

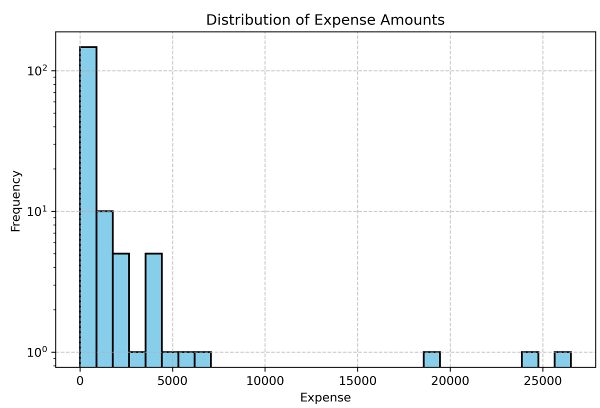

Fig. 1. Distribution of Expense Amounts.

Figure 1 shows the distribution of expense amounts. The distribution was right-skewed; therefore, a logarithmic scale was applied to improve visualization.

Expense amounts were categorized as follows:

- Small (< PHP 100): 67 transactions
- Medium (PHP 100–499): 65 transactions
- Large (PHP 500–999): 17 transactions
- Very Large (PHP 1,000–9,999): 22 transactions
- Extremely Large (≥ PHP 10,000): 3 transactions

Most transactions were small or medium-sized expenses.

E. Expense Distribution by Category

Figure 2 presents the percentage share of expenses by category.

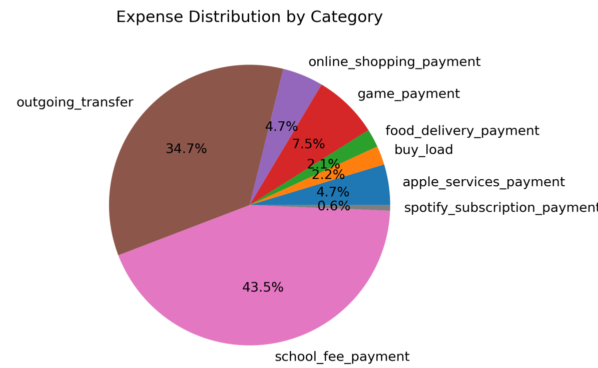

Fig. 2. Expense Distribution by Category.

School fee payments accounted for the largest proportion of total expenses (43.5%), followed by outgoing transfers (34.67%). Other categories contributed smaller proportions.

F. Spending by Category

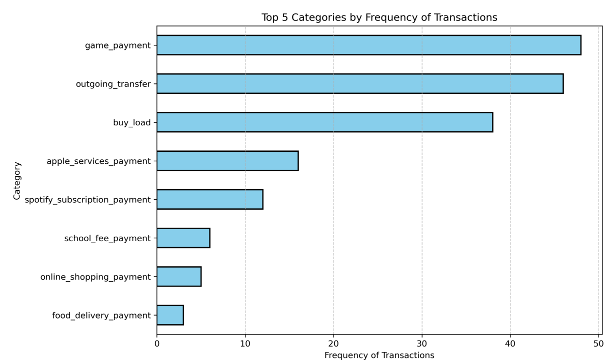

Fig. 3. Total Transaction by Category.

Figure 3 shows the distribution of expense transactions by category.

Most frequent categories:

- game_payment – 48 transactions
- outgoing_transfer – 46 transactions
- buy_load – 38 transactions

Although game payments occurred most frequently, they did not represent the largest share of total spending.

G. Highest Expense Transactions

Table V lists the five highest expense transactions recorded during the study period.

TABLE V
TOP FIVE HIGHEST EXPENSE TRANSACTIONS

Year-Month	Category	Amount (PHP)
2025-03	school_fee_payment	26,523.60
2025-07	school_fee_payment	24,039.60
2025-11	school_fee_payment	18,763.80
2025-07	outgoing_transfer	7,000.00
2025-08	outgoing_transfer	5,700.00

These high-value transactions contributed significantly to total spending.

H. Monthly Expense Trends

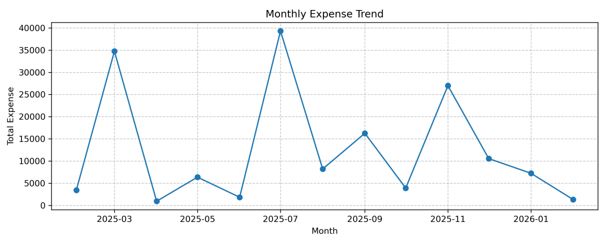

Fig. 4. Monthly Expense Trend.

Figure 4 presents the monthly expense totals over the study period. Spending fluctuated across months, with notable peaks and declines.

The highest spending month was:

- July 2025 – PHP 39,308.78

Lower spending months included April 2025 and February 2026.

I. Monthly Transaction Frequency

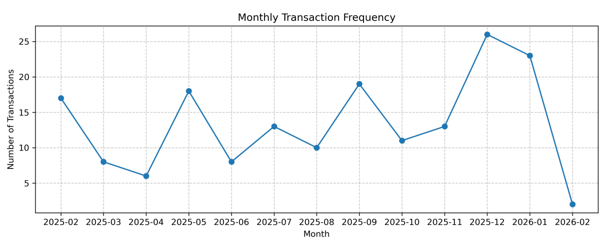

Fig. 5. Monthly Transaction Frequency.

Figure 5 illustrates the number of expense transactions per month. Transaction frequency peaked in December 2025 and January 2026, indicating increased spending activity during this period.

J. Weekday vs Weekend Spending

An independent samples t-test was conducted to determine whether a significant difference exists between weekday and weekend spending.

The hypotheses tested were:

- **H0:** There is no significant difference between weekday and weekend expense amounts.
- **H1:** There is a significant difference between weekday and weekend expense amounts.
- T-statistic: 1.92
- p-value: 0.0567

Since the p-value is greater than the 0.05 significance level, the null hypothesis cannot be rejected. This indicates that there is no statistically significant difference between weekday and weekend spending, although weekend expenses were slightly higher on average.

K. Relationship Between Transaction Frequency and Spending

Correlation analysis was performed to examine the relationship between transaction frequency and total spending per category. The correlation coefficient was:

- r = 0.105

This result indicates a very weak positive relationship, suggesting that categories with more transactions do not necessarily correspond to higher total spending.

L. Differences in Spending Across Categories

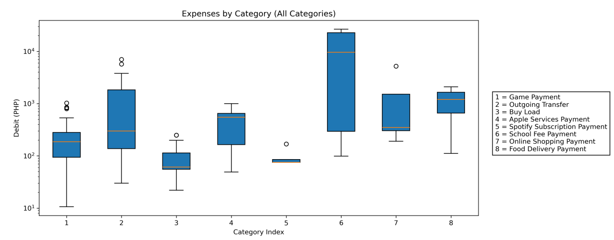

Fig. 6. Expenses by Category Box Plot.

Descriptive statistics were computed to compare expense amounts across categories. School fee payments recorded the highest average expenses, while mobile load and subscription payments showed lower and more consistent expense values.

A one-way analysis of variance (ANOVA) test was conducted to determine whether significant differences exist in expense amounts across spending categories.

The hypotheses tested were:

- **H0:** There is no significant difference in mean expense amounts across spending categories.
- **H1:** At least one spending category has a significantly different mean expense amount.
- F-statistic: 18.74
- p-value: 2.73×10^{-18}

Since the p-value is less than 0.05, the null hypothesis is rejected. This indicates that significant differences exist in expense amounts across categories.

M. Correlation Analysis

Figure 7 presents the correlation matrix among selected variables.

A strong positive correlation (r = 0.65) was observed between school fee payments and expense amounts, indicating that large expenses are strongly associated with this category.

Other variables showed weak correlations, suggesting limited relationships between time-based variables and expense magnitude.

V. Discussion

This study examined one year of personal GCash expense transactions to understand spending behavior, category distribution, temporal patterns, and statistical relationships. The discussion is organized according to the research questions of the study.

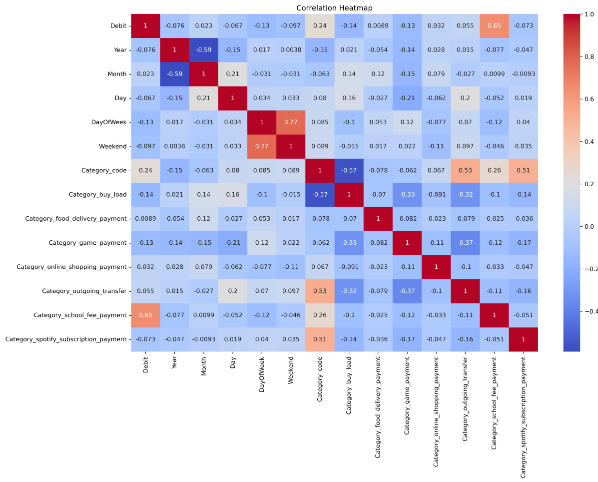

Fig. 7. Correlation Heatmap.

A. RQ1: Which categories account for the highest personal expenses?

The results indicate that total expenses were dominated by a small number of high-value categories. School fee payments accounted for the highest annual expenditure (PHP 70,152.00), followed by outgoing transfers (PHP 55,857.00). Combined, these categories represented the majority of total spending, demonstrating that infrequent but large financial obligations had the greatest influence on overall expenditure. In contrast, categories such as food delivery, buy load, and subscription payments contributed smaller shares of annual spending, suggesting that these were routine but lower-cost expenses.

B. RQ2: How frequently do expense transactions occur within each category?

Transaction frequency was highest for game payments, outgoing transfers, and buy load purchases. This pattern suggests that spending behavior included recurring low-to-medium cost transactions, particularly for digital entertainment and telecommunications services. However, frequent categories were not necessarily those with the highest total expenditure. For example, game payments were the most frequent but contributed substantially less to annual spending compared to school fee payments and outgoing transfers. This finding highlights that transaction frequency reflects routine behavioral habits, while total spending is largely shaped by high-value obligations.

C. RQ3: How do personal expenses change over time?

Monthly spending fluctuated across the year, indicating that expense behavior was not uniform over time. Peaks in monthly spending were associated with major financial obligations, particularly school fee payments and large transfers. The highest monthly expenditure occurred in July 2025 (PHP 39,308.78), suggesting a period of significant financial activity. Months with lower spending reflected periods without major obligations, reinforcing the observation that total expenses were driven primarily by occasional high-value transactions rather than consistent increases across time.

D. RQ4: What patterns can be observed in overall spending behavior?

Overall spending behavior was characterized by a right-skewed distribution of expenses. The median expense (PHP 161.24) was substantially lower than the mean (PHP 925.95), indicating that most transactions were small to medium in value, while a small number of high-value payments increased the overall average. This pattern is consistent with personal spending behavior where routine purchases occur frequently but major obligations dominate total expenditure.

In addition, transaction frequency increased during December 2025 and January 2026, suggesting seasonal patterns in spending activity. Although the dataset does not identify explicit reasons for this behavior, increased transaction frequency during these months may reflect end-of-year purchases or holiday-related spending.

E. RQ5: Are there significant differences or relationships in spending behavior across categories and time periods?

Statistical testing provided further evidence of differences and relationships in spending behavior. The independent samples t-test indicated no statistically significant difference between weekday and weekend spending ($p = 0.0567$), suggesting that expenses were relatively consistent throughout the week. Although weekend spending appeared slightly higher, the evidence was insufficient to conclude a meaningful weekday–weekend difference at the 0.05 significance level.

The ANOVA results confirmed statistically significant differences in expense amounts across categories ($p < 0.05$), indicating that spending categories represent distinct spending behaviors with different typical expense levels. School fee payments showed the highest average expenses compared to other categories such as buy load and subscription services, which were smaller and more consistent.

Correlation analysis showed a very weak relationship between transaction frequency and total spending ($r = 0.105$), reinforcing the idea that frequent transactions do not necessarily correspond to higher expenditure. The correlation heatmap also showed a stronger association between the school fee category and high expense amounts, consistent with the presence of large payments concentrated in this category.

F. Implications

The findings demonstrate that personal expense behavior in digital wallets is shaped by two major components: (1) frequent low-value transactions that represent routine spending habits, and (2) infrequent high-value transactions that dominate total expenditure. This distinction highlights the importance of monitoring both transaction frequency and category-level totals to improve financial awareness. Digital wallet records provide detailed transaction histories that can support budgeting decisions and encourage more mindful spending behavior when analyzed systematically.

G. Limitations and Future Work

This study is limited by its focus on a single participant (n = 1), which restricts generalizability. In addition, the dataset reflects only GCash transactions and does not account for expenses paid through cash or other platforms. Categorization relied on keyword matching, which may introduce classification errors for ambiguous descriptions. Future research may extend this work by including multiple participants, integrating other financial platforms, and exploring predictive models for expense forecasting and budgeting support.

VI. Conclusion

This study analyzed one year of personal GCash expense transactions to identify spending patterns and behavioral trends associated with digital wallet usage. The findings revealed that most expenses consisted of small and medium-value transactions such as mobile load purchases, gaming payments, and digital subscriptions. However, high-value expenses, particularly school fee payments and outgoing transfers, contributed the largest share of total spending and were responsible for peak monthly expenses. Spending levels fluctuated throughout the year, with the highest expenditures occurring in July 2025 and increased transaction activity observed during the final months of the year.

Statistical analysis indicated no significant difference between weekday and weekend spending, suggesting consistent spending behavior throughout the week. Correlation analysis showed a weak relationship between transaction frequency and total spending, while ANOVA results confirmed significant differences in expense amounts across categories. These findings highlight the importance of monitoring personal financial data, as frequent small expenses accumulate over time and major financial obligations significantly shape overall spending patterns. Digital wallet transaction analysis can therefore support improved financial awareness and more informed budgeting decisions.

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