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ANALYSIS OF THE EFFECT OF DIGITAL PRODUCT TYPES AND TRANSACTION FREQUENCY ON DIGITAL PRODUCT SALES IN TANGERANG THROUGH A DATA WAREHOUSE APPROACH

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ABSTRACT

The growth of the digital economy has made digital products such as prepaid credit, internet data, and game vouchers essential for urban communities, including in Tangerang City. This study aims to analyze the effect of digital product type and transaction frequency on digital product sales in Tangerang. A quantitative explanatory approach is applied using secondary data extracted from a retail partner's data warehouse and processed with Python in Google Colab. The sample consists of 200 digital product transactions in October 2025, selected using total sampling. Data are analyzed using multiple linear regression and classical assumption tests. The results show that transaction frequency has a positive and significant effect on sales; prepaid credit has a negative and significant effect compared to internet data, while game vouchers have a positive and significant effect on sales. An R-squared value of 9.04% indicates that other factors also influence sales. These findings highlight the importance of leveraging data warehouses to design data-driven strategies for improving digital product sales.

Keywords: digital product sales; product type; transaction frequency; data warehouse; Tangerang.

INTRODUCTION

The development of digital technology has changed the consumption patterns of Indonesians, especially in online-based economic activities. Digitalization has not only simplified transactions, but also created new consumption patterns that are fast and efficient. One sector that has experienced rapid growth is the sale of digital products such as phone credit, internet data packages, and game vouchers. These products have become essential to support the communication, connectivity, and entertainment activities of modern society. This shows that digital transformation has become an integral part of people's lives (Kementerian Komunikasi dan Informatika Republik Indonesia, 2023)

The city of Tangerang, as an area with high urbanization and internet penetration, has also experienced a significant increase in digital product transactions. Based on data from the Tangerang City Central Statistics Agency (BPS), there has been an increase in digital economic activity in line with the increase in mobile device users and internet access. The people of Tangerang are now increasingly accustomed to conducting online transactions to meet their daily needs, including the purchase of digital products. However, variations in characteristics between product types and different transaction frequencies are important factors that can affect sales levels and consumer purchasing behavior in this sector (Badan Pusat Statistik, 2024).

Each type of digital product has different purchasing characteristics. Mobile phone credit is generally purchased routinely and functionally, while internet quota is a primary need to support online activities. Meanwhile, game vouchers are more entertainment-oriented, where purchasing interest is greatly influenced by specific factors such as promotions and prices offered (Ridha & Daga, 2020). These differences in characteristics can affect transaction frequency and ultimately impact digital product sales.

The relevance of these product characteristic differences has been confirmed by a number of previous studies. In the functional product category, Saqdiyah & Patrikha (2023) found that the decision to purchase internet quota is strongly driven by rational factors such as price, service quality, and ease of use of the application. This finding differs from the pattern in entertainment products as revealed by Pauzi et al. (2023), which highlights that in the purchase of game vouchers (such as Valorant), the variables of promotion and price play a vital role in influencing purchase interest, which then leads to a purchase decision. On the other hand, in addition to product type, user behavior is also in the spotlight. Firdaus & Zuliestiana (2022), through a UTAUT 2 model analysis of Codashop top-up services, proved that habit is a strong predictor that influences service usage intensity. This indicates that transaction frequency is closely related to consumer behavior patterns.

Although various studies have discussed these aspects, research that specifically examines the comprehensive relationship between digital product types and transaction frequency on actual sales is still limited, especially in the Tangerang area. Most previous studies only highlight e-commerce in general without applying a data-based analytical approach (Komalasari et al., 2021).

Based on the review of the various previous studies above, it can be synthesized that studies on digital products are still fragmented. Most studies tend to discuss only one type of product separately—whether it is a specific focus on internet quotas or only on game vouchers—without comparing the characteristics of both in the same analytical framework. In addition, the majority of existing studies (such as Firdaus & Zuliestiana (2022); Pauzi et al. (2023); Saqdiyah & Patrikha, (2023) still rely heavily on survey methods to measure variables such as perception, interest, or behavioral intent, and not many utilize actual transaction data (actual purchase behavior).

Therefore, there is still a significant research gap that needs to be addressed. First, there has been no comprehensive study comparing the three main types of digital products, namely phone credit, data packages, and game vouchers, simultaneously in a single model. Second, there is still very limited research using real transaction data (e.g., from data warehouses) to analyze actual purchasing behavior at the retail level, rather than just survey perceptions. Third, existing studies tend to position frequency or intensity of use as the dependent variable (Y), while no study has specifically tested transaction frequency as an independent variable (X2) to see how much it affects total sales value (Y).

This study offers essential novelty by filling these gaps. It will analyze actual transaction data to directly compare the effects of three types of products (phone credit, data packages, and game vouchers) on sales, as well as test the effect of transaction frequency on sales value in a specific local context (Tangerang) with high digital activity.

Based on these conditions, this study was conducted with the aim of analyzing the influence of digital product types and transaction frequency on digital product sales in Tangerang using a data warehouse approach as an empirical analysis tool. This approach allows for more efficient processing and integration of large amounts of transaction data, resulting in accurate and in-depth information (Syaputra et al., 2022)Through this study, it is hoped that a more comprehensive understanding of digital consumer behavior and the factors that influence sales levels will be obtained, which can later become the basis for business actors in formulating effective data-based marketing strategies in the digital era.

Digital Product Concept

Digital products are non-physical goods or services that can be consumed or utilized through electronic devices such as computers and smartphones (Prasmul-ELI, 2024; Widyastuti et al., 2024). Unlike physical products, digital products lack a tangible form, as they are stored in electronic formats and delivered via the internet. Their primary value lies in the benefits and ease of access they provide to users, eliminating the need for physical distribution like shipping (Yovita, 2025).

Key characteristics of digital products include intangibility, scalability, no degradation in quality upon duplication, and instant delivery through digital networks (Retnowardhani, 2020). Common types encompass phone credit, internet data packages, game vouchers, e-books, software, digital subscriptions, and online courses (Prasmul-ELI, 2024). This study focuses on three primary types phone credit, internet data packages, and game vouchers due to their high transaction frequency in urban communities, aligning with the rapid growth in digital markets driven by technological advancements and increasing internet penetration in areas like Tangerang (Purba et al., 2021)

The emergence of digital payment platforms, such as GoPay, OVO, and Dana, has further facilitated these purchases Transfi, (2025), where service features and user experience significantly influence consumer decisions to use these platforms. Digital product sales refer to transactions conducted entirely through online platforms, encompassing product selection, payment, and delivery without physical interaction. Feriyanto et al. (2024) Success indicators include transaction volume, total sales value, purchase frequency, and customer retention rates (Sulistyo et al., 2025).

Digital product sales are influenced by key factors such as price, service quality, promotional activities, and user experience (Kotler & Keller, 2016; Laudon & Traver, 2021). Digital marketing strategies, including SEO, social media, and affiliate programs, enhance purchase interest and market reach (Kingsnorth, 2019; Pratama & Damayanti, 2025). Overall, digital products and sales are interconnected, offering practical value and efficient distribution. This research analyzes how product types and transaction frequency impact sales growth in Tangerang, building on the identified gaps in prior studies that often lack comparative analysis and actual transaction data.

Types of Digital Products: Phone Credit, Internet Data Packages, and Game Vouchers

Digital products encompass non-physical goods or services consumed directly via electronic devices like smartphones, computers, or tablets (Labamu, 2025). In the digital economy, they drive online transaction growth due to easy access, rapid distribution, and cost efficiency (Laudon & Traver, 2021). According to Sasabone et al. (2023) digital products feature instant delivery, non-tangible value, and reliance on digital distribution platforms. Consumer decisions are primarily influenced by utility and transaction ease rather than emotional factors, differing from conventional products.

This study examines three key digital product types prevalent in Indonesia's digital ecosystem: phone credit, internet data packages, and game vouchers. First, this is digital balance used for calls, SMS, and additional services like data packages or premium content. It serves routine, essential communication needs (Sellercraft, 2025). Second, these provide data access for online services such as social media, e-commerce, and productivity apps. They are functional and productive, supporting daily digital activities like work, education, and entertainment (Rizka, 2025). Third, these are digital credits for in-game purchases, virtual currencies, or premium features in online games. They are entertainment-oriented, influenced by lifestyle and personal interests (Amalia, 2025).

These product types, alongside transaction frequency and value, form interconnected components for analyzing consumption patterns and sales performance (Atika & Nasution, 2023). Their combination offers insights into consumer behavior, from basic needs and utility to entertainment preferences (Erlangga et al., 2024), addressing the variations highlighted in the introduction and prior research (e.g Pauzi et al., 2023; Saqdiyah & Patrikha, 2023)

Data Warehouse

A data warehouse is a centralized data storage system designed to collect, integrate, and analyze data from multiple sources over extended periods (Inmon, 2005). Unlike daily operational systems focused on transaction processing, it serves as a repository for historical data to support decision-making and strategic analysis (Imanda et al., 2024; Kimball et al., 2013). In digital product sales, data warehouses manage transaction data from platforms like e-commerce, digital wallets, and online payment systems. Through ETL (Extract, Transform, Load) processes, data is gathered, cleaned, and structured for in-depth, accurate analysis (GEM, 2022).

The structure typically includes three main components: data sources (e.g., transactions for phone credit, data packages, and game vouchers); data storage using models like star schema for efficient analysis; and an access layer for interactive reports and dashboards (Kimball et al., 2013).

Key functions in sales analysis involve data integration from digital sources, historical trend examination, improved report accuracy, and serving as a support tool for business decision-making in sales analysis (Sepsugiarto, 2011). This enables identification of relationships between product types, transaction frequency, and sales levels. In this study, the data warehouse approach facilitates systematic analysis of how product variations and transaction intensity affect digital product sales in Tangerang, overcoming limitations in prior survey-based studies.

Conceptual Framework

The digital economy has transformed transaction and consumption patterns, making products like phone credit, internet data packages, and game vouchers integral to daily life for their convenience and speed (Kotler & Keller, 2016). Each type offers distinct utility: phone credit for basic communication, data packages for connectivity, and game vouchers for entertainment (Sari & Pratama, 2022). These differences influence purchasing behavior and transaction values.

Transaction frequency also plays a critical role in sales levels, with higher frequencies indicating loyalty and engagement, potentially boosting overall sales (statista, 2022). Utilizing a data warehouse allows for accurate integration and analysis of actual transaction data from various platforms (Imanda et al., 2024).

Drawing from consumer behavior theory and digital economy concepts, it is assumed that digital product types and transaction frequency positively influence sales. Relevant product types meeting consumer needs, combined with high purchase frequency, enhance sales volume and value, addressing the research gaps in comprehensive, data-based comparisons.

Research Hypotheses

Based on the conceptual framework and literature review, the hypotheses for this dissertation are formulated as follows:

H1: Digital product types influence sales.
H2: Transaction frequency influences sales.
H3: Digital product types and transaction frequency simultaneously influence sales.

Empirical Study

Based on the theoretical study above, the relationship between variables can be described as follows.

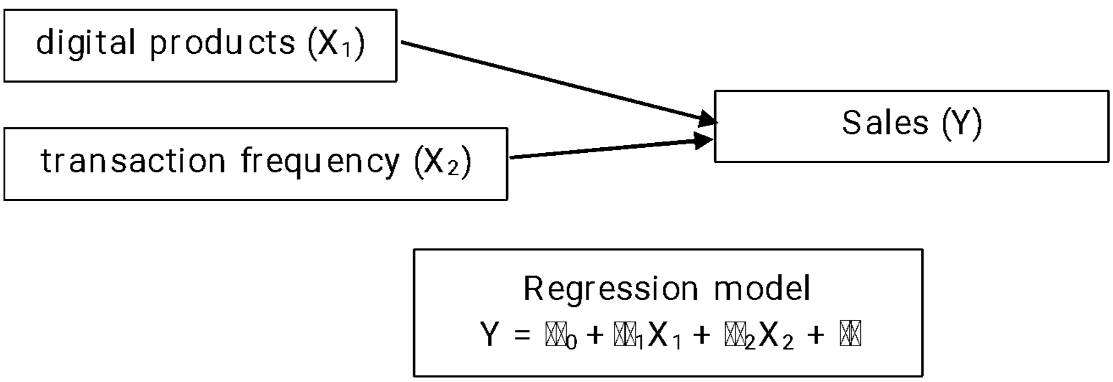

Figure 1. Regression Model

RESEARCH METHODS

Research Design

This study uses an observational quantitative design with an explanatory approach. The aim is to explain the causal relationship between the product type variable and the transaction frequency and value variables based on existing historical data without any intervention from the researcher.

Population and Sample

The population in this study includes all records of digital product sales transactions (phone credit, data packages, and game vouchers) from one or more distributors/retailers in the Tangerang area. The sample uses a total sampling technique (census), in which all transaction data recorded during the research period will be used as a sample. This is possible because the data comes from comprehensive digital logs.

Research Variables and Operational Definitions

Operational definitions of variables are used to clarify the concepts being studied and how they are measured so that they can be processed quantitatively. In this study, there are two independent variables, namely the type of digital product and the frequency of transactions, as well as one dependent variable, namely digital product sales.

Table 2. Operational Definitions of Variables

Variable	Operational Definition	Indicators	Source
Product Type (X1)	The categories of products transacted are coded as follows: 1=Mobile Credit, 2=Data Plan, 3=Game Voucher.	The type of product selected by the customer (Mobile Credit, Data Plan, Game Voucher).	The definition and indicators of sales variables are adapted from the concept of strategic marketing according to Tjiptono, F. & Chandra (2016)
Transaction Frequency (X2)	The total number of transactions occurring for each product type within a specific time period (e.g., per day).	Daily, weekly, or monthly transaction volume per product type.	Adapted from e-commerce transaction research (Statista, 2024)
Sales (Y)	Selling price (in Rupiah) for each individual transaction recorded in the system.	Total revenue from transactions per time period.	Adapted from (Kotler & Keller, 2016)

Data Collection Techniques

The data in this study is secondary data sourced from the data warehouse of digital product retail/distribution partners. Transaction data is first processed through an ETL (Extract, Transform, Load) process in the data warehouse environment, then exported to files (e.g., CSV) and further processed using Python in Google Colab for statistical analysis purposes.
The data period used is October 2025, with the main column structure consisting of transaction_id, timestamp, product_name, product_category, and price.

Table 3. Data Collection Techniques via Data Warehouse and Google Colab

Stage	Environment	Process Name	Main Activities	Output
1	Data Warehouse	Extract (Operational System → Data Warehouse)	Sales transaction data for digital products from the operational system (cashier/sales application) is extracted and collected into the data warehouse system through the company's internal ETL process.	Transaction data is stored in an integrated manner in the data warehouse.
2	Data Warehouse	Transform (Integration & Standardization)	Within the data warehouse, data from various sources is cleaned and standardized: alignment of table structures, data types, date formats, and consistency of product category naming.	Integrated and consistent transaction fact tables for digital product sales.

3	Data Warehouse	Load (Storage to Analytical Tables)	The transformation results are loaded into analytical tables (fact & dimension tables) in the data warehouse so that they are ready to be exported for further analysis.	Analytical transaction table (fact table) in the data warehouse.
4	Data Warehouse → Google Colab	Data Export	Transaction analytical tables in the data warehouse (October 2025 period) are exported to files (e.g., CSV/Excel) containing main columns such as transaction_id, timestamp, product_name, product_category, and price.	Transaction data files (CSV/Excel) exported from the data warehouse.
5	Google Colab (Python)	Import Data	The exported file from the data warehouse is uploaded to Google Colab and read using Python (pandas library).	The raw dataframe in Python contains transaction data from the data warehouse.
6	Google Colab (Python)	Selection & Sample Preparation	In Google Colab, data selection is performed according to research criteria (October 2025 period and product categories of Mobile Credit, Internet Quota, Game Vouchers), as well as limiting to 200 transactions that meet the analysis requirements.	The dataframe contains 200 selected transactions according to the research criteria.

Data Analysis Techniques

Data analysis is performed using statistical software such as Python or SPSS, following these sequential steps. First, descriptive statistics are calculated, including measures of central tendency (mean and median) and dispersion (standard deviation) for transaction values, along with frequency tables for the number of transactions per product type. Data visualization is achieved through bar charts and boxplots to provide an overview of the patterns. Before hypothesis testing, statistical assumption tests are conducted, comprising the Shapiro-Wilk normality test to determine if the dependent variable data (sales) follows a normal distribution, and the Levene's test for homogeneity of variance to assess whether variances across groups (based on digital product types) are equal, serving as prerequisites for ANOVA. For hypothesis testing, H1 (the effect of product type) is evaluated using One-Way ANOVA if normality and homogeneity assumptions are met; otherwise, the non-parametric Kruskal-Wallis test is applied, followed by the Tukey post-hoc test if ANOVA results are significant to identify specific group differences. For H2 (the effect of frequency), simple linear regression is employed to measure the magnitude and significance of transaction frequency's influence on digital product sales, with Spearman's correlation as an alternative if assumptions are not fulfilled. Additionally, OLS regression analysis models the impact of product type on transaction value by converting the product type variable into dummy variables, using phone credit as the reference category.

Flow Chart

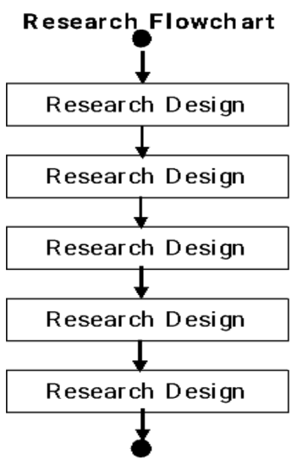

Figure 2. Research Flowchart

RESULTS AND DISCUSSION

Descriptive Analysis Results

Descriptive Statistics:

	Total Harga	Frekuensi Transaksi
count	200.000000	200.000000
mean	65425.000000	78.470000
std	44075.818357	20.389896
min	11000.000000	27.000000
25%	51000.000000	86.000000
50%	60000.000000	86.000000
75%	73000.000000	87.000000
max	303000.000000	87.000000

Figure 3. Descriptive Statistics

Descriptive statistics show that Total Price has a wide distribution, as seen from the very large range between the minimum and maximum values and the high standard deviation; in accordance with the concept of dispersion, the greater the range and standard deviation, the greater the variation in data in a distribution (LibreTexts Statistic, 2025).

This condition indicates the existence of several transactions with values that are much higher than most observations. In addition, the Total Price median being lower than the average suggests a right-skewed distribution and the possible existence of large outliers. Conversely, Transaction Frequency appears to be much more homogeneous because the quartile and maximum values are relatively close, indicating that most consumers conduct a similar number of transactions and that the variation in transaction frequency between consumers tends to be small and stable.

Relationship between Transaction Frequency and Sales

The scatter plot above shows that the relationship between transaction frequency and sales tends to be negative, as seen from the slightly downward regression line. In scatter plot analysis, a negative regression line slope is interpreted as a negative correlation, meaning that when the value of variable X increases, the value of variable Y tends to decrease (LibreTexts Statistic, 2025). The fairly wide and sparse distribution of points around the best-fit line also indicates that the strength of the relationship between the two is relatively weak, as a scattered pattern of points far from the line is generally associated with a weak or almost non-existent correlation. This is in line with the findings in the graph, where at low transaction frequencies, sales vary greatly (including several high-value transactions), while at high transaction frequencies, many sales points are concentrated in the lower range, indicating that other factors such as transaction value, product type, or transaction time are likely to determine total sales more than the number of transactions alone.

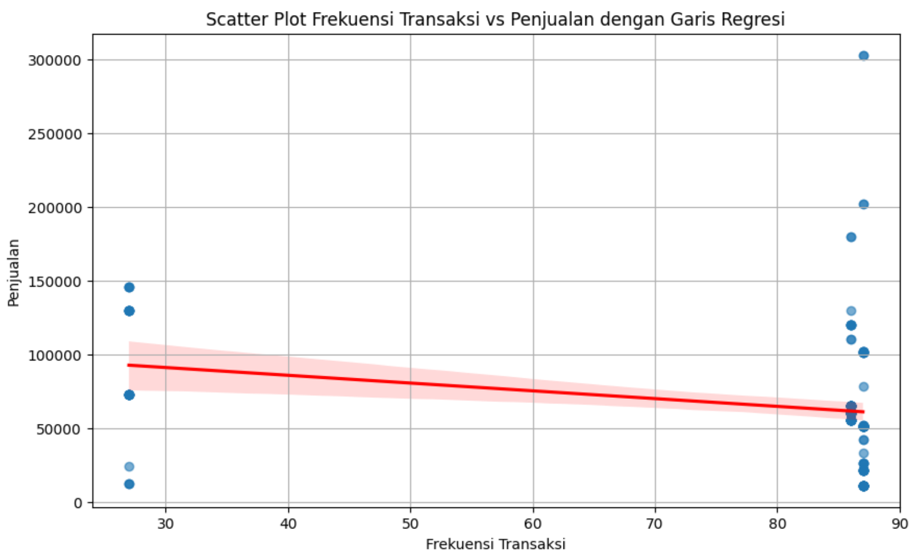

Figure 4. Relationship between Transaction Frequency and Sales

Sales Distribution Based on Digital Product Type

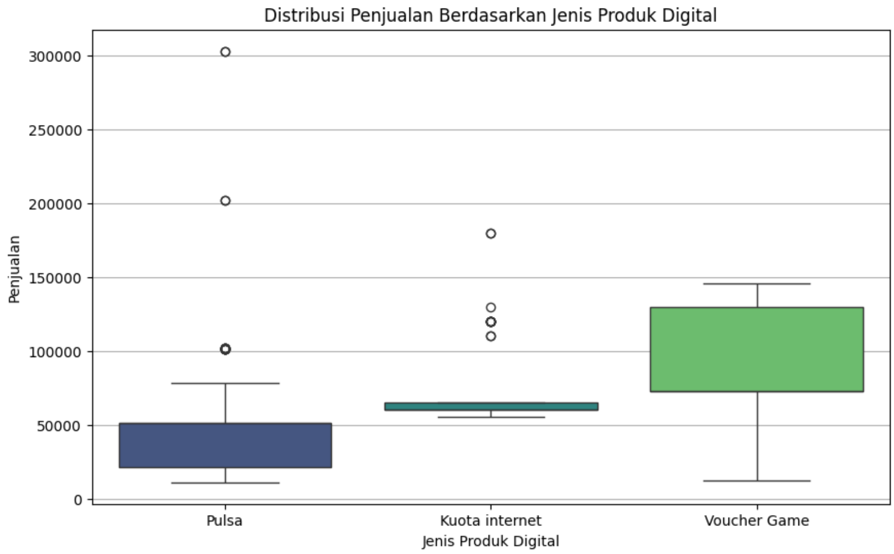

Figure 5. Sales Distribution Based on Digital Product Type

The boxplot visualization shows the differences in sales distribution for three types of digital products. Theoretically, a boxplot summarizes five important numbers (minimum, lower quartile, median, upper quartile, maximum) and facilitates comparison of the median, interquartile range (IQR) width, and the presence of outliers between several data groups (Frost, 2025). In the graph, Game Vouchers appear to have the highest median and the longest box and whiskers, which can be interpreted as the category with the highest sales and transaction value variation; the points outside the whiskers represent outliers, which are several transactions with very high sales values. Internet Quotas have a narrower box with a median in the middle range and without many outliers, indicating a more stable and consistent sales distribution. In contrast, the Credit category has the lowest median and distribution range compared to the other two categories; however, there are still several outliers at the top, indicating the existence of large but relatively rare transactions. Thus, visually, it can be concluded that Game Vouchers contribute the most to sales with high variability, Internet Quota is the most stable, while Credit tends to generate lower transaction values.

Classical Assumption Test
Residual Normality Test

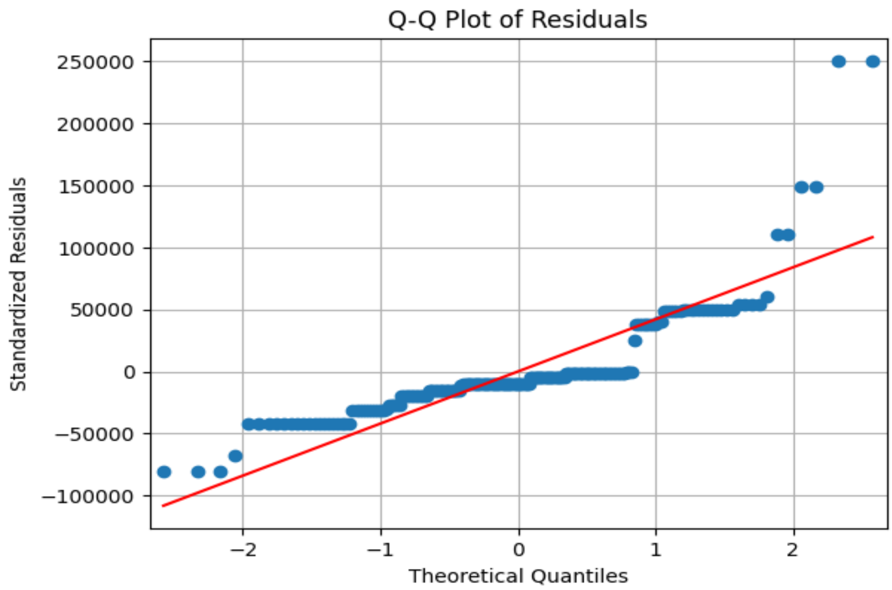

Figure 6. Residual Normality Test

Normality tests are performed to ensure that the residuals in the regression model follow a normal distribution, with two tests employed: the Shapiro-Wilk and Kolmogorov-Smirnov (K-S). The Shapiro-Wilk test yields a statistic of 0.7390 and a p-value of 0.0000, where the very small p-value (less than 0.05) indicates that the residuals are not normally distributed, signifying a significant difference between their distribution and the expected normal one. Similarly, the Kolmogorov-Smirnov test produces a statistic of 0.3070 and a p-value of 0.0000, consistent with the previous results and confirming that the residuals do not meet the normality assumption, as the p-value falls below 0.05.

The normality of residuals was tested using Shapiro–Wilk and Kolmogorov–Smirnov. Both tests produced p-values of 0.0000, which is less than 0.05, indicating that the residuals are not normally distributed. However, in OLS regression, normality is not a prerequisite for obtaining unbiased and efficient estimators. According to the Gauss–Markov theorem, as long as other assumptions are met, such as correct model specification, zero-mean error, homoscedasticity, and no autocorrelation, the OLS estimator remains BLUE (Best Linear Unbiased Estimator) even if the residuals are not normal. Modern literature also confirms that normality is not the most crucial assumption (Zygmont, 2023) shows that in medium to large sample sizes, the Central Limit Theorem keeps the statistical distribution of tests (t and F) valid, so that moderate violations of residual normality do not always weaken the validity of regression inference.

Multicollinearity Test

```
--- Uji Multikolinearitas ---

Hasil Uji Multikolinearitas (VIF):
                            variable       VIF
0                 Frekuensi Transaksi  2.066236
1          Jenis Produk Digital_Pulsa  2.035291
2  Jenis Produk Digital_Voucher Game  1.030945
```

Figure 7. Multicollinearity Test

Multicollinearity testing was performed using the Variance Inflation Factor (VIF) value. Based on the calculation results, the Transaction Frequency variable has a VIF value of 2.066, Digital Products with Credit has a value of 2.035, and Digital Products with Game Vouchers has a value of 1.030. All of these values are well below the general threshold of 5 used to detect multicollinearity. Gujarati (2009) explain that the use of VIF and the general limit of VIF < 10 indicates the absence of serious multicollinearity. Thus, it can be concluded that there is no significant multicollinearity in the model. Therefore, each independent variable provides different information and does not excessively influence each other, so the regression model can be considered stable and suitable for further analysis.

Heteroscedasticity Test

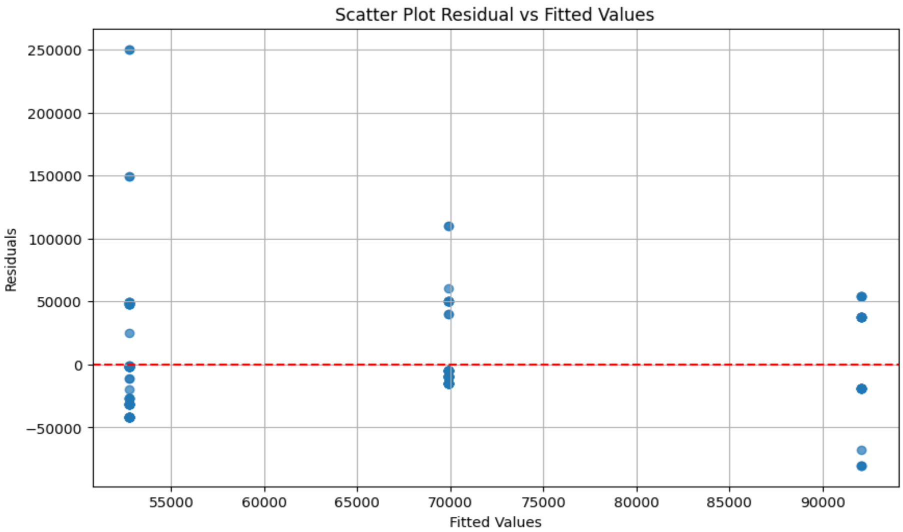

Figure 8. Heteroscedasticity Test

The Breusch–Pagan test results show that the p-value is 0.2116, which is above the significance threshold of 0.05. Therefore, the null hypothesis (H_0) stating that the residual variance is constant (homoscedasticity) cannot be rejected. In other words, there is no evidence of heteroscedasticity in the regression model. This finding is reinforced by the scatter plot of residuals against fitted values, which shows a pattern of points scattered randomly around the zero line without forming any particular pattern such as tapering or widening. Montgomery et al. (2021) explains visual inspection of residuals, including tapering/widening patterns as indications of heteroscedasticity. The combination of statistical test results and visual inspection supports that the model meets the homoscedasticity assumption, so the OLS (Ordinary Least Squares) coefficient estimates remain unchanged.

Multiple Linear Regression Analysis Results

```
Nilai R-squared: 0.0904
F-statistic: 9.79 (p-value: 0.0001)

Koefisien Regresi dan Nilai p:
=====================================================================================================
                                     coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------------
const                           3.288e+04   3844.456      8.552      0.000    2.53e+04    4.05e+04
Frekuensi Transaksi              430.3186     74.707      5.760      0.000     282.990     577.647
Jenis Produk Digital_Pulsa     -1.758e+04   6467.187     -2.718      0.007   -3.03e+04   -4824.604
Jenis Produk Digital_Voucher Game 4.762e+04 5618.604     8.475      0.000    3.65e+04    5.87e+04
=====================================================================================================
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Figure 9. Multiple Linear Regression

With the regression model $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \varepsilon$, the regression coefficient table provides the following values. The constant of 32.880 represents the predicted sales value when transaction frequency is 0 and the product type is the base category (internet quota), serving primarily as the model's baseline rather than carrying significant economic interpretation. The coefficient for transaction frequency, at 430.32, indicates that each additional transaction increases average sales by approximately Rp 430.32, assuming the digital product type remains constant (with X_2 and X_3 unchanged), reflecting a positive relationship where higher transaction frequency leads to greater sales value. For the pulsa dummy variable, the coefficient of –17,580 shows that, at the same transaction frequency, sales for phone credit are on average Rp 17,580 lower than the base category of internet quota, with the negative sign suggesting that credit generates smaller transaction values compared to quota. In contrast, the game voucher dummy coefficient of 47,620 means that, under the same transaction frequency, sales for game vouchers are on average Rp 47,620 higher than internet quota, with the positive and substantial value highlighting game vouchers as the product type contributing the highest sales among the three digital categories. Thus, from the regression equation, it can be concluded that sales will increase as transaction frequency rises, and the type of digital product significantly determines sales amounts, where game vouchers notably boost sales while phone credit tends to reduce sales value relative to internet quota.

Model Validity Evaluation (R-squared and F-statistic)

The regression model shows an R-squared value of 0.0904, which means that the Transaction Frequency and Digital Product Type variables can only explain 9.04% of the variation in sales. Although the contribution is small, the model still provides an important picture of the influence of each variable on sales.

In addition, the F-statistic value of 9.79 with a p-value of 0.0001 indicates that the model is simultaneously significant. Greene (2018) explains the function of the F-test to determine whether independent variables collectively have a significant effect on the dependent variable. This means that when Transaction Frequency and Digital Product Type are tested together, both are proven to have a significant effect on sales. Thus, the model can be considered suitable for use in analyzing the relationship between the two independent variables and sales.

Interpretation of Coefficients and Hypothesis Testing

The model employs dummy variables to distinguish between categories of digital products, allowing each coefficient to be interpreted by comparing it to the base category. As discussed by

Gujarati (2009), this involves the concept of dummy variables, reference categories (base categories), and the interpretation of dummy coefficients relative to the base category. Hypothesis testing is conducted based on the coefficient values and p-values of each independent variable. For transaction frequency on sales (H1), the coefficient of 430.32 with a p-value of 0.0000 indicates that this variable has a positive and significant effect on sales, meaning that every increase in one transaction will boost sales by 430.32 and confirming transaction frequency as an important factor contributing to increased sales, thus supporting Hypothesis 1 (H1). Regarding digital product type – mobile credit on sales (H2), the coefficient for digital product type_mobile credit is –17,578.41 with a p-value of 0.0072, indicating that mobile credit products have a negative and significant effect on sales compared to the base category, with this negative value showing that sales of mobile credit products tend to be lower, thereby supporting Hypothesis 2 (H2). Finally, for digital product type – game vouchers on sales (H3), the coefficient for digital products with game vouchers is 47,616.19 with a p-value of 0.0000, indicating that the game voucher category has a positive and significant effect on sales compared to the base category, with this large positive value illustrating that game vouchers are a category that can significantly increase sales, therefore supporting Hypothesis 3 (H3). Additional 4

Interpretation of Analysis Results and Discussion

Descriptively, the data shows that the Total Price variable has a very wide range of values, with a large difference between the minimum and maximum values and a high standard deviation. The median, which is below the mean, indicates a right-skewed distribution and the existence of a number of transactions with sales values much higher than the majority of observations. In contrast, Transaction Frequency appears more homogeneous because the quartile and maximum values are relatively close, meaning that most consumers conduct a similar number of transactions. The boxplot visualization reinforces these findings, namely that Game Vouchers have the highest median and sales range with many outliers, Internet Quotas show a more stable distribution in the middle range, while Mobile Credit has the lowest median and sales distribution.

In terms of model validity, multiple linear regression produced an R-squared value of 0.0904, which means that Transaction Frequency and Digital Product Type together can only explain approximately 9.04% of sales variation. Although this contribution is relatively small, the F-test shows that the model remains simultaneously significant with an F-statistic value of 9.79 and a p-value of 0.0001. The multicollinearity test using the Variance Inflation Factor shows a VIF value of 2.066 for Transaction Frequency, 2.035 for Credit, and 1.030 for Game Vouchers; all of which are well below the general threshold (5–10), indicating no serious multicollinearity. In addition, the Breusch–Pagan test yielded a p-value of 0.2116 (> 0.05), indicating no heteroscedasticity and supporting the homoscedasticity assumption of the model.

The Shapiro–Wilk and Kolmogorov–Smirnov tests of residual normality indicate that the residuals are not normally distributed. The Shapiro–Wilk statistic value is 0.7390 with a p-value of 0.0000 and the K–S statistic is 0.3070 with a p-value of 0.0000, both of which are below the significance level of 0.05, so the null hypothesis of normality is rejected. However, based on the Gauss–Markov Theorem and the Central Limit Theorem, with an adequate sample size and other assumptions (such as correct model specification, zero mean error, homoscedasticity, and no autocorrelation) fulfilled, the OLS estimator remains BLUE and the test statistic distribution approximates normal. Thus, the violation of residual normality in this study is not considered sufficient to invalidate the validity of the resulting regression inferences.

Partially, Transaction Frequency has been proven to have a positive and significant effect on sales. A regression coefficient of 430.32 with a p-value of 0.0000 indicates that every one-unit increase in transaction frequency is followed by an average increase in sales value of around Rp430.32 after controlling for the type of digital product. This finding aligns with the concept of digital consumer behavior, where transaction intensity reflects user needs and purchasing patterns. However, the scatter plot on the Relationship between Transaction Frequency and Sales shows a wide distribution of points and a simple regression line that tends to decline, so that the bivariate relationship between frequency and sales appears weak and even slightly negative. This condition indicates that the positive effect of Transaction Frequency is only clearly seen when product type heterogeneity is controlled in a multiple model.

The Digital Product Type variable has a significantly different effect on sales. Compared to the basic category (Internet Quota), the Credit dummy has a coefficient of –17.578.41 with a p-value of 0.0072, which indicates a negative and significant effect on sales; that is, transactions dominated by

Credit products tend to generate lower sales values. Conversely, the Game Voucher dummy has a coefficient of 47.616.19 with a p-value of 0.0000, indicating a positive and highly significant effect. These results are in line with the boxplot, which shows that the median and variation of Game Voucher sales are the highest, accompanied by many large outliers, while Internet Quota appears as the category with a stable sales pattern. Thus, Game Vouchers can be seen as the main contributor in terms of sales value, Internet Quota as a supporter of stability, and Pulsa as the category with relatively low transaction values.

Overall, the results of the study confirm that transaction frequency and type of digital product both have a significant effect on sales, but with different roles. Transaction frequency acts as a driver of sales accumulation on a moderate scale (coefficient 430.32; p-value 0.0000), while the product type structure, dominated by Game Vouchers (47,616.19; p-value 0.0000), Internet Quota stability, and a lower position for Credit (–17,578.41; p-value 0.0072), more strongly determines the sales value profile achieved. The relatively low R-squared value (9.04%) indicates that digital product sales are also influenced by various factors outside the model, such as product price, operator promotions, payment methods, and transaction timing (e.g., payday). These findings open up opportunities for further research to include these variables in order to improve the model's ability to explain sales variations.

CONCLUSIONS

This study shows that the type of digital product and transaction frequency have a significant effect on digital product sales in Tangerang. Transaction frequency has been proven to be the main driver of sales growth, while each product category shows different performance: Game Vouchers contribute the most to sales, Internet Quotas have a stable pattern, and Phone Credit is at the lowest position in line with its nominal characteristics. Although the model only explains 9.04% of sales variation, the regression model remains valid because no multicollinearity, heteroscedasticity, or autocorrelation was found, so the OLS estimates remain reliable. These findings confirm that digital product sales behavior is influenced by many external factors, but product type and transaction intensity remain important components in understanding the dynamics of the digital market. Based on the research results, retailers are advised to maximize their marketing strategies in the Game Voucher category through event-based promotions and bundling offers that have the potential to increase transaction value. For Internet Quota, strategies can focus on maintaining service consistency and stock availability because this category is routine and stable. Meanwhile, in the Credit category, a value-enhancement approach can be implemented through loyalty programs or low-cost bundling packages. Further research is recommended to include additional variables such as operator promotions, payment methods, purchase timing, or customer preferences so that the model can explain sales variations more comprehensively.

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