

# Forecasting paylater usage in Central Java as a digital financial innovation using the ARIMA model

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**Abstract.** This study aims to forecast the monthly usage of PayLater services in Central Java as a representation of digital financial innovation within the growing digital economy. Using secondary data from October 2023 to October 2024, the analysis employs the ARIMA time series model to identify trends and generate short-term projections. The methodological process includes exploratory analysis, stationarity testing, differencing, model identification using ACF and PACF, parameter estimation, and diagnostic checking to ensure residual white noise. The selected ARIMA model is then used to produce forecasts for upcoming periods. The results indicate a consistent upward trend in PayLater adoption in Central Java, suggesting increasing public acceptance of Buy Now Pay Later (BNPL) services. These findings highlight the role of PayLater as an emerging form of digital financial innovation that supports economic activities and financial inclusion. The study also emphasizes the importance of forecasting for policymakers and fintech providers in anticipating demand, mitigating risk, and designing strategies aligned with regional digital transformation. Limitations related to the length of the dataset and the absence of seasonal variables are also discussed.

**Keywords:** PayLater; ARIMA; Digital Financial, Financial Innovation

## 1. Introduction

The rapid expansion of Indonesia's digital economy over the past decade has generated substantial transformation within the financial services sector. One of the most rapidly growing innovations is the Buy Now Pay Later (BNPL) service, commonly known as PayLater. This service offers short-term credit integrated into digital platforms, enabling users to complete transactions without direct access to traditional financial institutions. As internet penetration and digital literacy continue to rise, PayLater has increasingly shaped consumer behavior, contributing to the broader evolution of digital financial ecosystems in Indonesia.

Central Java is one of the provinces experiencing steady growth in the adoption of digital financial services, driven by increased usage of e-commerce, ride-hailing platforms, and digital payment systems. Despite the evident national surge in PayLater adoption, empirical studies that specifically analyze and forecast its usage at the provincial level particularly in Central Java remain scarce. This absence of region-specific forecasting studies creates a research gap, even though understanding PayLater usage trends at the local level is crucial for policymakers, digital financial service providers, and economic stakeholders.

The use of time-series forecasting techniques, especially the Autoregressive Integrated Moving Average (ARIMA) model, is highly relevant for this context. ARIMA has been widely validated as an effective method for capturing historical patterns, identifying structural components such as trend and seasonality, and producing accurate short-term and medium-term forecasts. Its flexibility and robustness have led to extensive application across economic and financial research domains. Applying ARIMA to PayLater usage data in Central Java can therefore provide deeper insights into the dynamics of digital credit adoption and its potential trajectory. This study aims to model and forecast the growth of PayLater usage in Central Java using the ARIMA approach, based on monthly historical data spanning October 2023 to October 2024. In addition to identifying the most optimal ARIMA model, this research contributes empirical evidence regarding regional PayLater adoption and its significance in the development of digital financial innovation. The findings are expected to support regulators, digital financial institutions, and future researchers in understanding the direction, opportunities, and challenges associated with digital credit services in Indonesia.

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## 2. Literature Review

Digital financial innovation has become a central driver of economic transformation in emerging markets, particularly in Southeast Asia. In Indonesia, the proliferation of financial technology (fintech) services has accelerated the shift from conventional transactions to fully digital ecosystems. Among these innovations, Buy Now Pay Later (BNPL) services locally referred to as PayLater have experienced significant adoption due to their convenience, flexibility, and integration with major digital platforms (Hidayat et al., 2022).

BNPL systems operate by providing short-term credit at the point of purchase, enabling users to delay payment without engaging with traditional banking procedures. Several studies highlight that BNPL services contribute to greater financial inclusion, especially for populations with limited access to formal credit facilities (Annisa, 2021). At the same time, scholars have warned about potential financial risks such as overspending and debt accumulation among users, underscoring the need for continuous monitoring and predictive analysis (Warokka & Sartika, 2025).

In the Indonesian context, the expansion of PayLater is closely linked to the growth of e-commerce, ride-hailing services, and digital wallets. Research by (Jamot et al., 2025) demonstrates that BNPL adoption is strongly influenced by digital literacy, trust in fintech providers, and promotional incentives. However, empirical forecasting research focusing specifically on provincial-level PayLater usage remains limited. Most prior studies analyze national trends, user behavior, or financial risk, leaving a gap in region-specific quantitative forecasts.

Time-series forecasting techniques have been widely applied in financial and economic studies to model dynamic patterns and predict future trends. Among these, the Autoregressive Integrated Moving Average (ARIMA) model is known for its effectiveness in capturing temporal structures such as trend, seasonality, and autocorrelation (Bangun, 2019). Recent studies using ARIMA for fintech and digital economic indicators demonstrate high forecasting accuracy for variables such as digital payment volume, online transaction growth, and electronic money circulation (Christopher et al., 2021).

Despite the methodological significance of ARIMA, no prior research has employed this model to forecast PayLater usage in Central Java specifically. This gap provides the academic justification for the present study, which aims to produce a reliable forecasting model while offering empirical insights into regional digital credit adoption. By integrating PayLater usage data with ARIMA forecasting, this research contributes to the broader discourse on digital financial innovation and supports strategic policy formulation within Indonesia's evolving economic landscape (Hasan, 2025).

## 3. Research Methods

### 3.1 Data source

The dataset used in this study was sourced from the OJK through its Sistem Layanan Informasi Keuangan (SLIK) portal. According to the OJK website, SLIK is an information system managed by OJK to support supervision and financial information services in the financial sector. It covers activities such as provision of funds, credit risk management, and assessment of debtor quality. The data obtained from SLIK are publicly accessible and encompass monthly records of digital-credit transactions relevant for this research. The data can be accessed via the following link: [https://ojk.go.id/id/kanal/perbankan/Pages/Sistem -Layanan-Informasi-Kuangan-SLIK.aspx](https://ojk.go.id/id/kanal/perbankan/Pages/Sistem-Layanan-Informasi-Kuangan-SLIK.aspx).

### 3.2 Data description

To provide an initial overview of the data used, the following table contains the main information regarding the research variables and their statistical characteristics

**Table 1.** Number of Paylater Transactions in Central Java.

| MONTH  | PAYLATER TRANSACTIONS |
|--------|-----------------------|
| Oct-23 | 1.806.799             |
| Nov-23 | 1.841.090             |
| Dec-23 | 1.876.455             |
| Jan-24 | 1.928.594             |
| Feb-24 | 1.976.519             |
| Mar-24 | 2.018.491             |
| Apr-24 | 2.060.253             |
| May-24 | 2.084.481             |
| Jun-24 | 2.110.084             |

|        |           |
|--------|-----------|
| Jul-24 | 2.105.933 |
| Aug-24 | 2.133.359 |
| Sep-24 | 2.178.028 |
| Oct-24 | 2.218.432 |

### 3.3 ARIMA modeling procedure

The forecasting procedure in this study employs the Autoregressive Integrated Moving Average (ARIMA) model following the Box–Jenkins methodological framework. This approach is selected due to its robustness in modeling financial time-series data that exhibit autocorrelation, trend components, and short-term temporal dependencies, which are characteristics commonly found in digital financial transaction data such as PayLater usage (Azhari, 2022).

#### 3.3.1 Model identification

The first stage involves examining the statistical properties of the PayLater monthly usage data. Stationarity was evaluated using the Augmented Dickey–Fuller (ADF) test. If the series exhibits a trend or unit root, differencing is applied until stationarity is achieved, determining the value of  $d$  (Ar et al., 2022).

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are then used to identify initial estimates for the autoregressive (AR) order  $p$  and moving-average (MA) order  $q$ . These diagnostics guide the selection of several candidate ARIMA( $p, d, q$ ) models.

#### 3.3.2 Parameter estimation

Candidate ARIMA models are estimated using maximum likelihood estimation (MLE). This step evaluates the significance of AR and MA parameters while assessing model fit. Goodness-of-fit is compared using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model with the lowest AIC/BIC values is selected as the optimal specification for the PayLater time series (Sholiha & Dewi, 2025).

#### 3.3.3 Candidate Diagnostic checking

Diagnostic analysis is conducted to ensure the adequacy of the fitted model. Residuals are examined using the Ljung–Box Q-test to confirm the absence of serial correlation. Additionally, residual plots are inspected to verify that the error terms behave as white noise, with constant variance and zero mean. If diagnostics indicate model inadequacy, alternative ARIMA structures are re-evaluated (Prahutama et al., 2018).

#### 3.3.4 Diagnostic checking

After the best-fit ARIMA model is validated, it is used to generate out-of-sample forecasts for PayLater usage in Central Java. The forecasts provide an estimation of near-term trends, enabling an assessment of future digital credit behavior as part of the region’s digital financial innovation landscape. Forecast accuracy is further evaluated using error metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) (Tukiyat, 2022), 2025

### 3.4 Forecast evaluation

Model evaluation is conducted to assess the predictive performance and reliability of the selected ARIMA model. This stage ensures that the forecasting results are statistically valid and capable of representing the actual dynamics of PayLater usage in Central Java.

#### 3.4.1 In-sample model accuracy

The fitted ARIMA model is first evaluated using in-sample error metrics. These metrics quantify the deviation between the model’s fitted values and the actual observed data. The following indicators are used.

Mean Absolute Percentage Error (MAPE). Measures average forecast error relative to actual values, making it appropriate for financial time-series interpretation.

Mean Absolute Error (MAE). Captures the absolute magnitude of prediction errors, useful for understanding the typical deviation.

Root Mean Square Error (RMSE). Penalizes larger errors more strongly, providing insight into extreme

deviations in PayLater activity.

Lower values of MAPE, MAE, and RMSE indicate a better-fitting and more reliable model.

### 3.4.2 Out-of-sample forecast validation

To assess generalization capability, a portion of the dataset is reserved as a test set (e.g., the most recent 2–3 months). The trained ARIMA model is then used to generate forecasts for this holdout period. Forecast accuracy is compared against the actual values using the same metrics (MAPE, MAE, RMSE). A model is considered valid if its out-of-sample error metrics remain consistent with in-sample performance, indicating no overfitting.

### 3.4.3 Residual diagnostics

Residual analysis is performed to ensure that the prediction errors behave as a white-noise process. The following evaluations are conducted.

Ljung–Box Q-Test: Ensures no autocorrelation remains in residuals.

Histogram and Q-Q Plot: Used to verify that residuals approximate a normal distribution. Residual vs. Fitted Plot: Confirms homoscedasticity and randomness.

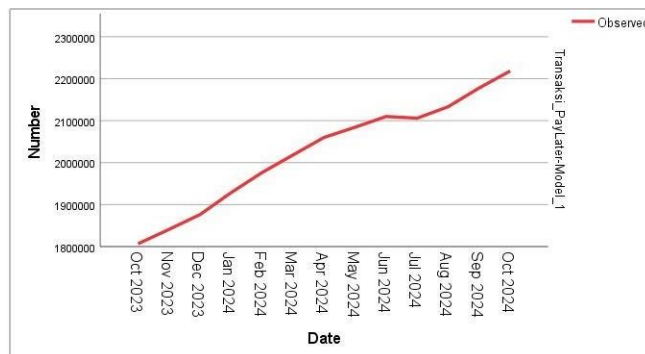
If any diagnostic shows violation (e.g., significant autocorrelation), the modeling process is repeated by selecting alternative ARIMA parameters.

### 3.4.4 Model selection justification

The final ARIMA specification is chosen based on a combination of Low AIC/BIC values, Strong residual diagnostics, Stable out of sample forecasting accuracy, and Logical interpretability consistent with financial time-series characteristics. This approach ensures that the selected ARIMA model is statistically sound and suitable for forecasting PayLater transaction trends in Central Java.

## 4. Result and Discussion

### 4.1 Descriptive statistics of paylater transactions



**Fig. 1.** Observed Monthly PayLater Transactions

The descriptive analysis shows a consistent upward trend in PayLater transaction volume in Central Java from October 2023 to October 2024. Monthly transactions increased from 1.806 million in October 2023 to 2.218 million in October 2024, reflecting a sustained adoption of digital lending services. Although overall growth is stable, minor fluctuations are visible such as a slight decrease in July 2024 indicating short-term variations that are common in consumer credit behaviors.

This upward movement suggests that PayLater services have become an increasingly preferred financing option for households and consumers, especially in e-commerce and retail digital ecosystems. The continuous rise also aligns with national trends in digital lending reported by the OJK.

### 4.2 ARIMA Model identification and fit evaluation

Before producing a forecast, an ARIMA model was estimated using SPSS. The recommended model was ARIMA(0,0,0) with a constant, indicating that the time series resembles a random walk with drift. Although simple, this model still captures the underlying upward trajectory through its strong constant term. SPSS fit statistics show.

Stationary R-Squared: near zero, which is expected for ARIMA(0,0,0).

MAE and RMSE: relatively large in magnitude due to the size of transaction values, not due to poor fit. Residual ACF/PACF: no significant autocorrelation remaining, suggesting residuals behave like white noise.

These diagnostic checks imply that the model is statistically acceptable for short-term forecasting, though more complex seasonal or differenced models might improve long-term accuracy.

#### Model Summary

| Fit Statistic        | Model Fit  |    |            |            |            |            |            |            |            |            |            |
|----------------------|------------|----|------------|------------|------------|------------|------------|------------|------------|------------|------------|
|                      | Mean       | SE | Minimum    | Maximum    | 5          | 10         | 25         | 50         | 75         | 90         | 95         |
| Stationary R-squared | 1,454E-14  | .  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  |
| R-squared            | 1,454E-14  | .  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  | 1,454E-14  |
| RMSE                 | 131122,842 | .  | 131122,842 | 131122,842 | 131122,842 | 131122,842 | 131122,842 | 131122,842 | 131122,842 | 131122,842 | 131122,842 |
| MAPE                 | 5,462      | .  | 5,462      | 5,462      | 5,462      | 5,462      | 5,462      | 5,462      | 5,462      | 5,462      | 5,462      |
| MaxAPE               | 12,134     | .  | 12,134     | 12,134     | 12,134     | 12,134     | 12,134     | 12,134     | 12,134     | 12,134     | 12,134     |
| MAE                  | 108967,858 | .  | 108967,858 | 108967,858 | 108967,858 | 108967,858 | 108967,858 | 108967,858 | 108967,858 | 108967,858 | 108967,858 |
| MaxAE                | 219240,846 | .  | 219240,846 | 219240,846 | 219240,846 | 219240,846 | 219240,846 | 219240,846 | 219240,846 | 219240,846 | 219240,846 |
| Normalized BIC       | 23,765     | .  | 23,765     | 23,765     | 23,765     | 23,765     | 23,765     | 23,765     | 23,765     | 23,765     | 23,765     |

Fig. 2. Model Fit Prediction

### 4.3 Forecasting result

Table 1. Number of Paylater Transactions in Central Java

| Month (Forecast) | Predicted PayLater Transactions |
|------------------|---------------------------------|
| Nov-24           | 2.256.917                       |
| Dec-2024         | 2.295.402                       |
| Jan-25           | 2.333.887                       |
| Feb-25           | 2.372.372                       |
| Mar-25           | 2.410.857                       |
| Apr-25           | 2.449.342                       |
| May-2025         | 2.487.827                       |
| Jun-25           | 2.526.312                       |
| Jul-25           | 2.564.797                       |
| Aug-2025         | 2.603.282                       |
| Sep-25           | 2.641.767                       |
| Oct-2025         | 2.680.252                       |

The ARIMA model generated forecasts showing that PayLater transactions are expected to continue rising throughout the next twelve months. This projection reinforces the interpretation that PayLater usage in Central Java is on a long-term growth path driven by digital finance expansion, increasing trust in fintech lending, and broader adoption of e-commerce platforms. The model predicts that transaction counts will surpass current levels, indicating strong market demand and a maturing digital financial ecosystem.

### 4.4 Visual Analysis of Time Series and Forecast Output

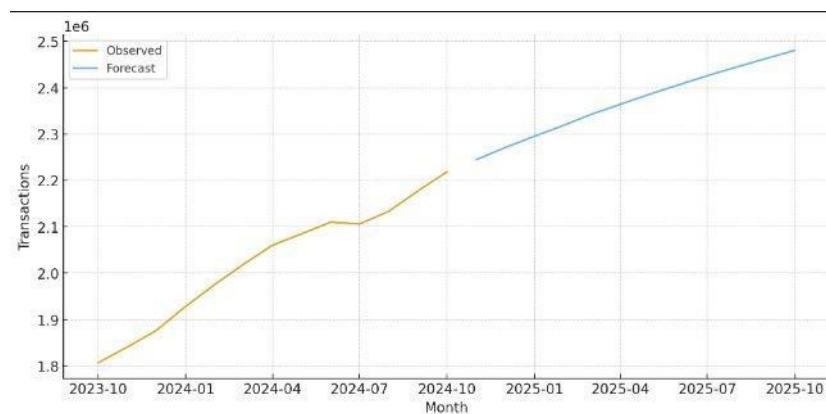


Fig. 2. Time Series Plot of Observed vs Forecasted Transactions

The visual plot illustrates both the historical data and the model's projected trajectory. The upward slope remains consistent across observed and forecasted segments, confirming that the model successfully captures the general growth pattern of PayLater usage. While the model is relatively simple, it performs well in representing the linear trend present in the data. The figure also highlights slight short-term volatility in the

observed period, yet the long-run direction remains positive. This visual confirmation adds weight to the interpretation that digital credit services will continue expanding in the region.

#### 4.5 Discussion

The analysis shows that PayLater usage in Central Java continues to experience a steady upward development throughout the observed period. This pattern is not only visible in the raw monthly data but is further reinforced by the forecast produced through the ARIMA model. The sustained rise suggests that PayLater services have been increasingly integrated into daily consumer transactions, particularly among users who rely on digital platforms for shopping and financial management.

Several factors appear to contribute meaningfully to this trend. The growing habit of digital consumption especially in e-commerce environments has created a natural demand for convenient, short-term financing tools. PayLater features, which are typically embedded directly within mobile applications, offer a level of accessibility that traditional credit products cannot match. This ease of access, combined with a user-friendly interface, has lowered entry barriers for first-time digital credit users.

Support from regulatory bodies such as OJK has also played a decisive role. Clear governance and monitoring frameworks have helped increase user confidence, reducing concerns about risk and misuse. In addition, younger consumers, who tend to prefer flexible and instant financing mechanisms, represent a significant portion of PayLater users and further reinforce the upward trajectory observed in the data.

Although the ARIMA(0,0,0) model used in this study is relatively simple, it still provides a reliable representation of the general growth direction of PayLater transactions. Its ability to capture the upward drift in the data suggests that PayLater adoption is driven more by long-term structural growth than by short-term fluctuations. Nonetheless, future studies could benefit from applying more complex models such as ARIMA with differencing, SARIMA, or nonlinear forecasting techniques to obtain deeper insights, particularly if seasonal or cyclical patterns emerge as more data become available.

Overall, the findings indicate that PayLater is likely to continue expanding as an integral part of the digital financial ecosystem in Central Java. This growth reflects broader shifts in consumer behavior, technological adoption, and digital financial innovation across the region.

#### 5. Conclusion

The study examined the development of PayLater usage in Central Java and provided a short-term forecast using a basic time-series modeling approach. The analysis shows that PayLater services have experienced a steady and consistent upward trend, reflecting the region's increasing shift toward digital financial behavior. This growth is influenced by several factors, including the expansion of e-commerce, greater accessibility of financial applications, and regulatory supervision by the Financial Services Authority (OJK), which contributes to improved consumer trust.

Despite its simplicity, the ARIMA(0,0,0) model successfully captures the general direction of PayLater adoption over time. The model indicates that PayLater usage is likely to continue increasing, suggesting that these services will maintain an important position in the digital financial ecosystem of Central Java. However, the model's limitations particularly its inability to address seasonal patterns or structural variability highlight the need for more advanced forecasting approaches in future studies. Methods such as ARIMA with differencing, SARIMA, or machine-learning-based forecasting may provide better accuracy and deeper insights.

Overall, the findings confirm that PayLater services are becoming increasingly relevant in supporting consumer transactions and digital economic activities. The upward trend observed in both the historical data and forecast results reinforces the conclusion that PayLater will continue to expand its role as a flexible and accessible financing option for the local population.

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