Annual International Conference
on Islamic Economics and Business, 2025, 53-70

Forecasting Indonesia's Digital Economic Growth Through QRIS Transaction Volume using the ARIMA Method

Maharani Najla Khonsanova[1] [1], *Reno* Ardy Syahputra[2], *Mafu* Ceesay[3], *Bayu* Nurhadi[4]

[1,2,3] Faculty Tarbiyah and Teacher Education, Universitas Islam Negeri Salatiga, Indonesia
[4] Faculty of Islamic Economics and Business, Universitas Islam Negeri Salatiga, Indonesia

Abstract. The development of digital technology has brought about significant changes in payment systems in Indonesia, particularly through the implementation of the Indonesian Standard Quick Response Code (QRIS). From 2022 to 2025, the use of QRIS has experienced rapid growth, as reflected in the increase in the number of users, merchants, and transaction intensity. This situation requires in-depth analysis to project future transaction volumes. This study aims to analyse historical patterns and forecast QRIS transaction volumes using the Autoregressive Integrated Moving Average (ARIMA) method with quarterly data from 2022Q1 to 2025Q2. Following the Box–Jenkins approach, the study includes stationarity testing, model identification, estimation, diagnostic testing, and forecasting. The ADF test results show that the data becomes stationary at second-order differencing (d=2). Of the various models, ARIMA(0,2,1) was selected as the best model based on the lowest AIC and SIC values and the highest adjusted R-squared, as well as meeting all diagnostic tests. The forecasting results show a strong upward trend in QRIS transaction volumes until 2027, with projections reaching 4,779 trillion rupiah. These findings confirm the potential of QRIS digitalisation in driving financial inclusion, empowering MSMEs, and accelerating Indonesia's economic growth.

Keywords: QRIS, Economic Growth ,Time Series Analysis ,Forecasting, ARIMA model

1 Introduction

The rapid development of information technology and digital payment systems has changed the way people and businesses conduct transactions, and has provided a major boost to the growth of the digital economy in Indonesia. One of the key innovations in this transformation is the Quick Response Code Indonesian Standard (QRIS), which was developed and launched by Bank Indonesia together with the Indonesian Payment System Association in 2019. (Bank Indonesia, 2023) QRIS is designed to integrate various payment service providers to make transactions more inclusive and accessible. With the increasing adoption of digital technology in society and the growing number of smartphone users, the volume of QRIS

[1] Corresponding author: nurhadi@uinsalatiga.ac.id

transactions has shown significant growth from year to year. Official data from the Indonesian Payment System Association shows an increase in the number of merchants, users, and transaction intensity, demonstrating that QRIS has become an important part of the digital economy ecosystem. The convenience and variety of QRIS features support digital economic and financial inclusion and strengthen cross-border payment connectivity, benefiting users and merchants, especially the MSME segment. As of June 2023, QRIS has been used by 26.7 million merchants, 91.4% of which are MSMEs. Transaction volume throughout 2022 reached 1.03 billion, an 86% increase year-on-year. Furthermore, the following data was obtained from the Indonesian Payment Systems Association website.

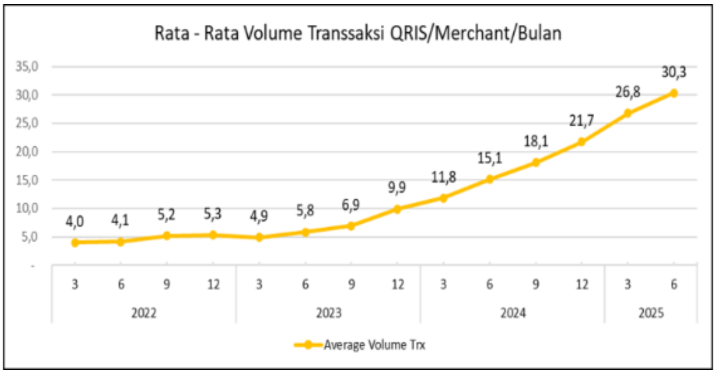


Figure 1: Average transaction volume per month for merchants or users

QRIS development data shows a rapid increase in usage throughout 2022–2025. In 2022, transaction intensity was still low at around 4–5 transactions per merchant per month. Since 2023, it has risen to nearly 10 transactions per month, then increased dramatically in 2024 to 21.7. In 2025, the average will reach 30.3 transactions per merchant per month. This trend shows the increasingly intensive use of QRIS as a daily payment instrument, not only for small-value transactions but also as a new habit in the digital payment ecosystem.

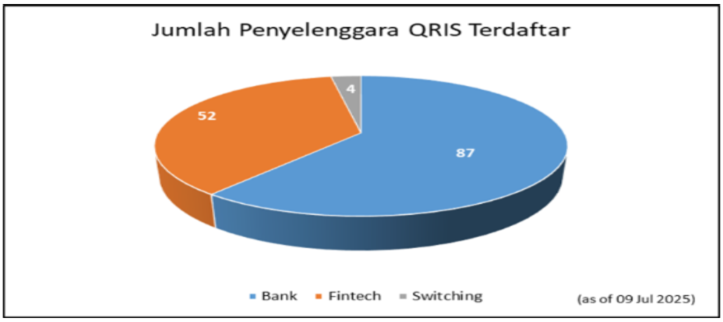


Figure 2: Pie diagram showing the number of QRIS users

As can be seen from the image, the number of QRIS providers has reached 143 entities, consisting of 87 banks, 52 fintech companies, and 4 switching companies. This illustrates that industry support for QRIS is growing, not only from the banking sector but also from fintech companies, which play an important role in driving innovation and expanding access to digital payment services.

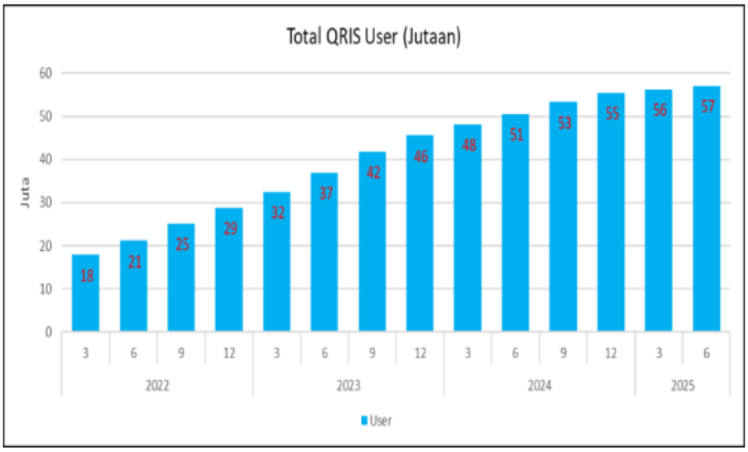


Figure 3: Number of QRIS codes in millions

The growth in the number of QRIS users also shows a positive trend. From 18 million users at the beginning of 2022, the number has increased sharply to more than 57 million in mid 2025. This surge reflects the increasing public acceptance of digital payments, while also demonstrating the success of the QRIS ecosystem in providing services that are easy, fast, and inclusive.

This growth has made the analysis and forecasting of QRIS transaction volumes a strategic issue, particularly in supporting the formulation of financial digitisation policies, the development of payment services, and the optimisation of the role of MSMEs in the digital economy. One of the statistical approaches widely used in analysing time series data is the Autoregressive Integrated Moving Average (ARIMA) model. This model is capable of capturing historical patterns in data, including trends and autocorrelation, and is therefore often used for short-term forecasting. Thus, this study aims to analyse historical patterns and predict QRIS transaction volumes using the ARIMA model.

2 LITERATUR REVIEW

2.1 Study on Digital Payment Systems and QRIS

Digital payment systems are one of the main foundations of a technology-based economy. The digitisation of payments not only increases transaction efficiency but also expands financial inclusion and supports broader economic activity in society. According to Rachman et al. (2024), the increase in the use of digital payment instruments is influenced by developments in information technology, changes in public preferences, and the growing need for fast and practical transactions.

QRIS, as a national standard for QR Code-based payments, was introduced to simplify and integrate various payment systems. Yani (2025) states that QRIS has a positive impact on Indonesia's digital sovereignty by facilitating domestic transactions and opening up opportunities for cross-border payment integration. The rapid growth of QRIS users and merchants reflects that the public is increasingly comfortable using digital payment services as part of their daily economic activities.

2.2 Study on Time Series Forecasting

Time series analysis is an approach used to understand data that changes over time. Data in time series is usually obtained periodically, such as hourly, daily, weekly, monthly, quarterly, and annually. This approach assists researchers and policymakers in making predictions and plans for the future. In order to select the appropriate forecasting method, the patterns in the data must first be understood. Generally, time series patterns are divided into four categories, namely seasonal, cyclical, trend, and random components. Seasonal patterns describe recurring fluctuations within a yearly period, for example in the form of quarterly, monthly, weekly, or daily patterns. In stochastic modelling, various approaches can be used, such as AR, MA, ARMA, ARIMA, and SARIMA models, to capture the characteristics of the data more accurately. (Atman Maulana, 2018).

Time series forecasting is a method used to estimate future values based on historical data patterns. This approach is commonly used in economics, finance, and payment systems because it is able to describe the dynamics of data over time. Time series models are widely used in economic policy research, including for analysing digital transactions, inflation, consumption, and various other macroeconomic indicators. The advantage of this method lies in its ability to rely on actual past data as the basis for predictions.

2.3 ARIMA in Analysis and Forecasting

Autoregressive Integrated Moving Average (ARIMA) is one of the most popular time series methods due to its ability to handle non-stationary data through the differencing process. Asrirawan (2022) explains that ARIMA components consist of autoregressive (AR), integrated (I), and moving average (MA), each of which functions to capture the dependence of past values and error patterns that appear in the data.

Hassyddiqy (2023) states that ARIMA excels at short-term forecasting because this model works directly based on historical patterns without requiring external variables. Tan (2020) adds that ARIMA has been widely used in digital economy studies, such as forecasting electronic transactions, due to its flexible characteristics and ability to adjust to data structures.

With the help of software such as EViews, the process of identifying, estimating, and diagnosing ARIMA models can be carried out systematically. Thus, ARIMA is a relevant and effective method for predicting the volume of QRIS transactions, which continues to grow and is influenced by time dynamics.

3 RESEARCH METHODOLOGY

3.1. Research Design

The purpose of this study is to predict the future volume of QRIS transactions in Indonesia based on historical data patterns. The analysis method used is the ARIMA (Autoregressive Integrated Moving Average) time series model, also known as the Box-Jenkins methodology.

Similar to previous research conducted by Asrirawan (2022), this study uses a quantitative method with a time series approach. Time series analysis is a statistical method that utilises sequential data patterns according to time, assuming inter-period dependence, such as in daily sales data, rainfall, or the spread of pandemic diseases. Time series data is usually measured in specific time intervals, and the main objectives of this analysis include identifying movement patterns over time, controlling systems, and forecasting future events. ARIMA has proven to be effective for short-term forecasting, as it can capture relatively dynamic data fluctuations. Conversely, ARIMA is less optimal for long-term forecasting, as the data tends to be stable or constant. The ARIMA modelling procedure according to Box-Jenkins involves four main stages, namely model identification, parameter estimation, diagnostic checks, and forecasting.

3.2. Type and Source of Data

The data used in this study is quarterly time series secondary data. The research variable is the QRIS Transaction Volume in Indonesia (in trillions of rupiah). The actual data used covers the period from Quarter 1 (Q1) 2022 to Quarter 2 (Q2) 2025, so that the total data observations used for model formation are 14 observations.

3.3. Analysis Method: ARIMA (Box-Jenkins)

Data analysis was performed using the ARIMA(p,d,q) model, which consists of three components:
1. Autoregressive (p): Indicates the dependence of data values on previous periods.
2. Integrated (d): Indicates the amount of differencing required for the data to become stationary.
3. Moving Average (q): Indicates the dependence of data values on the forecasting error (residual) from the previous period.

The entire data analysis and processing process in this study was carried out using EViews software.

3.4. Data Analysis Stages

The analysis process for constructing the ARIMA forecasting model follows the Box-Jenkins methodology stages as follows:

3.4.1 Stationarity Test (Identification of Order “d”)

The first stage is to ensure that the time series data is stationary, meaning that it has a constant mean and variance. The stationarity test is performed using the Augmented Dickey-Fuller (ADF) Test with the criterion that if the probability value (p-value) is < 0.05, then the data is stationary.

3.4.2 Model Identification (Identification of Order “p” and “q”)

This stage aims to determine the AR (p) and MA (q) orders by observing the Correlogram pattern (ACF and PACF graphs) of the stationary data.

3.4.3 Estimation and Selection of the Best Model

The model is estimated and selected based on the following criteria:
1) The smallest Akaike Info Criterion (AIC) and Schwarz Criterion (SC) values.
2) The largest Adjusted R-Squared value.

3.4.4 Diagnostic Testing (Model Validation)

The selected model is then tested diagnostically to ensure that it is valid and meets classical assumptions (also known as goodness-of-fit). Testing is performed on the model residuals.

1) Normality Test
   Using the Jarque-Bera test, if the p-value is > 0.05, then H0 is accepted, which means that the residuals are normally distributed.
2) Autocorrelation Test
   Autocorrelation is analysed through a correlogram using the Ljung–Box Q-Statistic. The residuals are said to be free of autocorrelation if all ACF and PACF values are within the confidence interval, and the p-value at each lag exceeds 0.05. This condition indicates that the model has captured all the dependency structures in the data, so that the residuals are random.
3) Heteroscedasticity Test
   If all p-values are greater than 0.05, then the null hypothesis is not rejected. This means that the residual variance is stable over time and does not form a variance clustering pattern. Thus, the residuals can be considered homoscedastic and the model does not experience heteroscedasticity problems.
4) Model Stability
   Model stability is tested by examining the inverse roots of AR/MA. A model is considered stable if all characteristic roots have a modulus value of less than 1 and are located within the unit circle. Fulfilment of these conditions indicates that the model dynamics are controlled and that the response to disturbances will subside over time, meaning that the model is suitable for use in forecasting.

3.4.5 Forecasting (Forecasting)

The ARIMA model that has met all testing criteria is then used in EViews to forecast values for the next period.

4 RESULTS AND DISCUSSION

The first step is to identify whether the data is stationary in mean and variance. Identification is carried out by examining the visual pattern of the data through a time series plot (Ariyanto & Tamam, 2020). Previous studies also explain that before building an ARIMA model, data identification is necessary. The first step is to ensure that the data is stationary, both in terms of mean and variance. This examination is generally done through time series visualisation, as time series plots can show whether there are changes in trends or fluctuations in variance. A time series is considered stationary if there is no shift in the mean or pattern of dispersion that changes over time (Muhammad Fahmuddin S, Ruliana Ruliana, 2023).

Table 1 : Descriptive statistics table for data Q1 off 2022 to the Q2 2025

	Data
Mean	403.3571
Median	251.0000
Maximum	1192.000
Minimum	66.00000
Std. Dev.	368.9692
Skewness	0.994545
Kurtosis	2.694966
Jarque-Bera	2.362222
Probability	0.306937
Sum	5647.000
Sum Sq. Dev.	1769797.
Observations	14

This study utilises data from the first quarter (Q1) of 2022 to the second quarter (Q2) of 2025. Based on QRIS transaction volume data collected over 14 observation periods, the following data distribution was obtained. The data shows an average (mean) QRIS transaction volume of 403.36 million transactions with a median value of 251 million transactions. The transaction value range is very wide, as seen from the minimum value of 66 and maximum value of 1,192 million transactions. This range reflects significant growth in several quarters, resulting in fluctuating data dynamics. This is in line with the standard deviation value of 368.97, which indicates significant variation in the data from the mean value.

The data was then plotted to provide an initial overview of the patterns and trends in transaction volume over time, enabling researchers to assess stationarity, detect anomalies, and ensure that the data was suitable for further analysis in ARIMA modelling.

The plot shows the data distribution pattern during the research period.

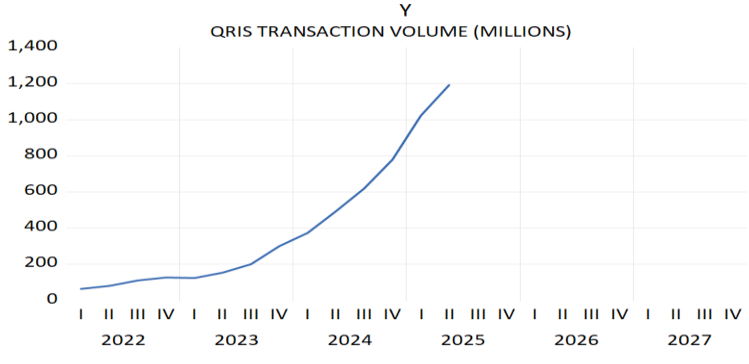


Figure 4: The plot shows QRIS transaction volume trends from Q1 2022 to Q2 2025.

The plot shows the movement of QRIS transaction volumes from the first quarter of 2022 to the second quarter of 2025. Visually, there is a very strong upward trend throughout the observation period. In the early stages of 2022, growth was relatively slow with small changes in volume between quarters. Entering 2023, the rate of increase became more apparent, marked by consistent acceleration in growth. This trend steepened sharply in 2024 to early 2025, as seen in the increasingly large and exponential quarterly increases.

This pattern indicates that the data is non-stationary, both in terms of mean and variance. The continuous increase shows that the average of the data changes over time, which is a common characteristic of time series with deterministic trends or structural growth. In addition, there are no extreme fluctuations that deviate from the general pattern, so there are no visual indications of anomalies or outliers in the plot. The plot provides an initial indication that the data has a strong trend structure, so before applying ARIMA modelling, a transformation or differentiation process is required to address the non-stationarity.

The following are the steps of ARIMA analysis (Box–Jenkins method) commonly used in time series research:

4.1 Stationarity Test

The stationarity test on time series data in this study was conducted using the unit root test. In statistics and econometrics, the most commonly used method to detect the presence of a unit root is the Augmented Dickey–Fuller (ADF) test. (Febiola et al., 2024)

The first step is to ensure that the time series data is stationary, meaning it has a constant mean and variance. The stationarity test was performed using the Augmented Dickey-Fuller (ADF) Test with the criterion that if the probability value (p-value) < 0.05, then the data is stationary.

4.1.1. Stationarity Test Results at Level

Table 2: Stationary Test Results

Null Hypothesis: Y has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		6.667435	1.0000
Test critical values:	1% level	-4.057910	
	5% level	-3.119910	
	10% level	-2.701103	

The ADF test results on the level data show a Prob. value of 1.0000, which is greater than 0.05. This means that the data is not stationary at the level. The next step is to analyse the stationarity of the first difference data or first order.

4.1.2 Stationarity Test Results on First Difference

Table 3: Result of the first stationary difference level test

Null Hypothesis: D(Y) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.840345	0.7698
Test critical values:	1% level	-4.121990	
	5% level	-3.144920	
	10% level	-2.713751	

The stationarity test results on level data using the ADF Test above show that the Test value on First Difference (d=1). First differencing was performed, but the ADF test results showed a Prob. value of 0.7698, which is still greater than 0.05. The data is still not stationary on the first difference. Therefore, the next step is to analyse the stationarity on Second Difference data or second order.

4.1.3 Second Difference unit root test results

Table 4. Results of the second stationary difference level test

Null Hypothesis: D(Y,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.408619	0.0073
Test critical values:	1% level	-4.200056	
	5% level	-3.175352	
	10% level	-2.728985	

Test on Second Difference (d=2) or second differencing. The ADF test results show a Prob. value of 0.0073, which is less than 0.05.

The conclusion from this stage is that the data becomes stationary after undergoing a two-step differencing process, so that the value of d = 2 is determined. Further analysis uses the ARIMA(p,2,q) model.

4.2 Model Identification (Identification of Orders "p" and "q")

ARIMA model identification analysis is carried out by observing patterns in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). ACF patterns are used to determine the possible order of the Moving Average (MA) component, while PACF patterns serve to identify the order of the Autoregressive (AR) component. (Nur Aisyah Indarningsih & Hasbi, 2022).

The correlogram is an important stage in time series analysis, especially in the ARIMA model identification process in the Box–Jenkins method. At this stage, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are used to observe serial correlation patterns in the data. ACF serves to measure the strength of the relationship between an observation and values in previous periods, while PACF describes the partial correlation between times after the influence of intermediate lags is controlled.

The following are the results of the correlogram test at the second difference level using Eviews.

Table 5. Corellogram test results table

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.388	-0.388	2.2964	0.130
		2	-0.004	-0.182	2.2967	0.317
		3	-0.010	-0.100	2.2986	0.513
		4	-0.207	-0.309	3.1990	0.525
		5	0.334	0.142	5.8698	0.319
		6	-0.195	-0.059	6.9358	0.327
		7	0.043	-0.032	6.9987	0.429
		8	-0.239	-0.366	9.3954	0.310
		9	0.042	-0.185	9.4939	0.393
		10	0.146	-0.128	11.279	0.336
		11	-0.022	-0.010	11.357	0.414

Based on the results of the correlogram analysis, the autocorrelation pattern in the ACF graph shows that significant values only appear at lag 1, while at subsequent lags the autocorrelation values appear small and no longer significant. This condition indicates that the moving average (MA) component in the ARIMA model is likely only needed up to order one, or even has a value of 0 if its effect is insignificant.

Meanwhile, the PACF graph shows that prominent values only exist at the first lag. At subsequent lags, the PACF values decrease and do not show significant significance. This pattern indicates that the autoregressive (AR) component also tends to be at order one or can also be zero.

Considering that the data has undergone a two-step differencing process, the appropriate ARIMA model structure is d = 2 with p and q values in the range of 0 to 1. Therefore, several relevant models for further analysis include ARIMA(1,2,1), ARIMA(1,2,0), ARIMA(0,2,1), and ARIMA(0,2,0) as options for observing the movement pattern of QRIS transaction volume.

4. 3 Estimation and Selection of the Best Model

The next step is to estimate the four models ARIMA(0,2,0), ARIMA(1,2,1), ARIMA(1,2,0), and ARIMA(0,2,1) using the Maximum Likelihood Estimation (MLE) approach. After the estimation process, the best model is selected by comparing a number of statistical measures, namely the smallest Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values, as well as the largest Adjusted R-Squared value.

In the study by Yuliawanti et al (2021), once several ARIMA models have been identified and all meet the basic modelling assumptions, the next step is to select the most optimal model. Determining the best model is usually done by comparing the Akaike Information Criterion (AIC) values, where the model with the lowest AIC value is considered to have the best fit to the data and is more efficient to use in the forecasting process.

4.3.1 ARIMA model (1,2,1)

Table 6. ARIMA (1,2,1) model results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.01055	3.268968	5.203644	0.0008
AR(1)	0.157016	0.618154	0.254009	0.8059
MA(1)	-0.999998	36631.75	-2.73E-05	1.0000
SIGMASQ	912.1117	990294.5	0.000921	0.9993
R-squared	0.426973	Mean dependent var		13.08333
Adjusted R-squared	0.212088	S.D. dependent var		41.67070
S.E. of regression	36.98875	Akaike info criterion		10.51002
Sum squared resid	10945.34	Schwarz criterion		10.67165
Log likelihood	-59.06010	Hannan-Quinn criter.		10.45017
F-statistic	1.986983	Durbin-Watson stat		1.955499
Prob(F-statistic)	0.194586			
Inverted AR Roots	.16			
Inverted MA Roots	1.00			

4.3.2. ARIMA model (1,2,0)

Table 6. ARIMA (1,2,1) model results
Table 7. ARIMA (1,2,0) model results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.60679	7.294573	2.139506	0.0611
AR(1)	-0.561473	0.316631	-1.773273	0.1099
SIGMASQ	1199.469	513.0030	2.338132	0.0442
R-squared	0.246443	Mean dependent var		13.08333
Adjusted R-squared	0.078986	S.D. dependent var		41.67070
S.E. of regression	39.99114	Akaike info criterion		10.45907
Sum squared resid	14393.62	Schwarz criterion		10.58030
Log likelihood	-59.75442	Hannan-Quinn criter.		10.41419
F-statistic	1.471681	Durbin-Watson stat		2.052208
Prob(F-statistic)	0.279912			
Inverted AR Roots	-.56			

4.3.3 ARIMA model (0,2,1)

Table 8. ARIMA (0,2,1) model results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.35714	2.823587	6.147197	0.0002
MA(1)	-0.999999	27463.35	-3.64E-05	1.0000
SIGMASQ	908.3232	726844.6	0.001250	0.9990
R-squared	0.429353	Mean dependent var		13.08333
Adjusted R-squared	0.302543	S.D. dependent var		41.67070
S.E. of regression	34.80083	Akaike info criterion		10.36322
Sum squared resid	10899.88	Schwarz criterion		10.48445
Log likelihood	-59.17933	Hannan-Quinn criter.		10.31834
F-statistic	3.385787	Durbin-Watson stat		1.707758
Prob(F-statistic)	0.080104			
Inverted MA Roots	1.00			

4.3.4 ARIMA model (0,2,0)

Table 9. ARIMA (0,2,0) model results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.08333	12.02929	1.087623	0.3000

R-squared	0.000000	Mean dependent var	13.08333
Adjusted R-squared	0.000000	S.D. dependent var	41.67070
S.E. of regression	41.67070	Akaike info criterion	10.37713
Sum squared resid	19100.92	Schwarz criterion	10.41754
Log likelihood	-61.26277	Hannan-Quinn criter.	10.36217
Durbin-Watson stat	2.404125		

Table 10. Comparison of 4 models

Model	Adjusted R-Squared	AIC	SIC
ARIMA (0,2,0)	0,000000	10,37713	10,41754
ARIMA (1,2,1)	0,212088	10,51002	10,67165
ARIMA (1,2,0)	0,078986	10,45907	10,58030
ARIMA (0,2,1)	0,302543	10,36322	10,48445

Based on the summary in Table 10, the ARIMA (0,2,1) model is the best model with the highest Adjusted R-Squared value and the lowest AIC and SIC values.

4.4 Diagnostic Tests

The ARIMA model is considered valid for use in forecasting if it meets a series of diagnostic tests that ensure the quality of the model. First, the residuals must follow a normal distribution; second, there should be no autocorrelation in the residuals; third, the residual variance must be homogeneous or free from heteroscedasticity; and fourth, the model must demonstrate stability through inverse root testing. If all these criteria are met, the model can be considered to satisfy the necessary statistical assumptions, making the resulting projections more reliable.

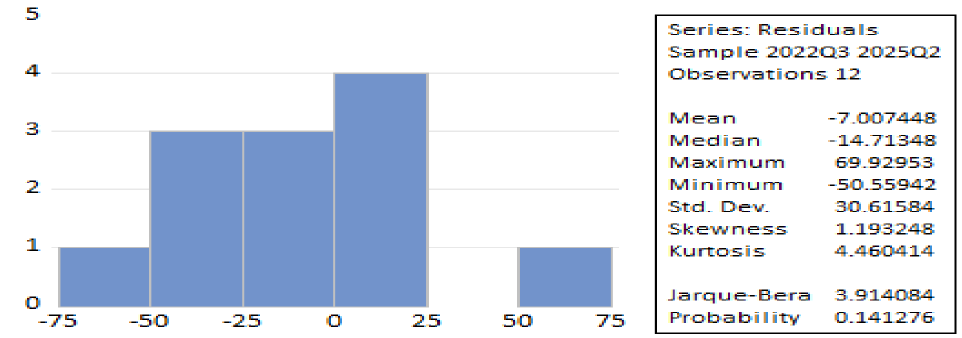
These findings are in line with the research by Yuliawanti et al. (2021), which confirms that the ARIMA model can only be used for accurate predictions if the residuals are random (white noise).

4.4.1 Normality Test

The normality test aims to ensure that the residuals from the ARIMA model are normally distributed. The normality of residuals is important because a good forecasting model must produce random errors that follow a normal distribution.

In ARIMA, normality is generally tested using the Jarque–Bera test. If the probability value (p-value) > 0.05, then the residuals can be considered normally distributed at a significance level of 5%. Normal residuals indicate that the model does not leave any particular patterns and has captured the data structure well.

Table 11. Normality test results



The Jarque-Bera normality test results for the residuals show a p-value of 0.141276, which is greater than the significance threshold of 0.05. Thus, H_0 is accepted, and the residuals can be said to be normally distributed. Conversely, if the p-value ≤ 0.05, then H_1 is accepted, indicating that the residuals do not follow a normal distribution.

4.4.2 Autocorrelation Test

The autocorrelation test aims to evaluate whether the residuals still have interperiod correlations. In a good ARIMA model, the residuals should form white noise, which is random and uncorrelated. The test is performed using the Residual Correlogram (ACF/PACF). The following are the results of the Residual Correlogram test.

Table 12. Autocorrelation test results

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.086	0.086	0.1122	
		2	0.064	0.057	0.1804	0.671
		3	-0.015	-0.025	0.1846	0.912
		4	-0.117	-0.118	0.4705	0.925
		5	0.190	0.217	1.3391	0.855
		6	-0.195	-0.234	2.4032	0.791
		7	-0.172	-0.171	3.3963	0.758
		8	-0.333	-0.317	8.0553	0.328
		9	-0.080	0.050	8.4162	0.394
		10	0.082	0.017	8.9801	0.439
		11	-0.010	0.029	8.9963	0.532

Based on the residual correlogram results, the ACF and PACF values at all lags appear small and do not exceed the significance limit, as indicated by the bars remaining within the dotted line. This pattern shows that there is no significant autocorrelation in the model residuals. These findings indicate that the model can be used.

4.4.3 Heteroscedasticity Test

The heteroscedasticity test aims to examine whether the residual variance is constant over time. In ARIMA, the assumption of constant variance is important to ensure that the model is unbiased in projecting volatility.

Table 13. Hetorocedasticity test results

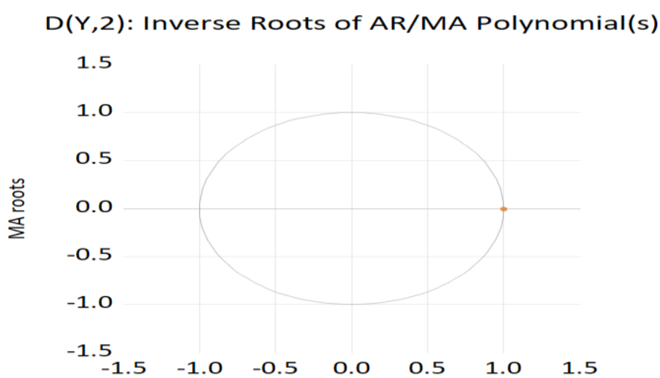
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.168	-0.168	0.4317	0.511
		2	-0.150	-0.183	0.8083	0.668
		3	-0.127	-0.200	1.1099	0.775
		4	0.063	-0.037	1.1943	0.879
		5	-0.127	-0.198	1.5807	0.904
		6	-0.101	-0.224	1.8636	0.932
		7	-0.057	-0.241	1.9728	0.961
		8	0.337	0.162	6.7324	0.566
		9	-0.034	-0.018	6.7968	0.658
		10	-0.156	-0.162	8.8490	0.546
		11	0.020	-0.022	8.9131	0.630

Based on the above output, all ACF and PACF values are within the significance limits and do not show any consistent or regular patterns. This condition indicates that the residual variance is stable over time and does not show signs of variance clustering, which usually leads to heteroscedasticity. In addition, all p-values in the Ljung–Box test are greater than 0.05, so H_0 is not rejected. This indicates that the residuals do not have significant autocorrelation and their variance does not form a specific pattern. Thus, the residuals can be considered to satisfy the assumption of homoscedasticity, so the model does not face heteroscedasticity issues.

4.4.4 Model Stability

ARIMA model stability refers to the consistency of parameters in the long term. A stable model has the characteristic that the characteristic roots (AR and MA roots) are within the unit circle. The model is declared stable if all points are within the unit circle. If there are points outside the circle, the model is considered unstable and unsuitable for use in forecasting, because the model response may deviate or explode over time.

Table 14. model stability results



The model stability test was observed from the Inverse Roots of MA. The results showed that the roots were within the unit circle (modulus value < 1). Thus, the ARIMA(0,2,1) model can be categorised as stable and suitable for analysis and forecasting because it has met the system stability requirements in the Box–Jenkins approach.

4.5 Forecasting

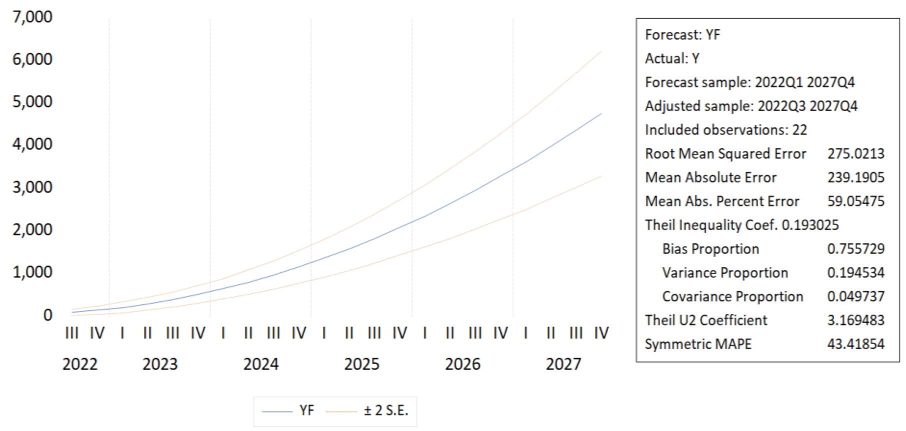


Figure 5: forecasting result

Table 15. comparison of actual data results with forecasted data

Waktu	Data Aktual	Hasil Peramalan
2022Q1	66	NA
2022Q2	80	NA
2022Q3	112	111.3571
2022Q4	128	160.0714
2023Q1	125	226.1429
2023Q2	155	309.5714
2023Q3	201	410.3571
2023Q4	301	528.5000
2024Q1	374	664.0000
2024Q2	494	816.8571
2024Q3	619	987.0714
2024Q4	779	1174.643
2025Q1	1021	1379.571
2025Q2	1192	1601.857
2025Q3	NA	1841.500
2025Q4	NA	2098.500
2026Q1	NA	2372.857
2026Q2	NA	2664.571
2026Q3	NA	2973.643
2026Q4	NA	3300.071
2027Q1	NA	3643.857
2027Q2	NA	4005.000
2027Q3	NA	4383.500
2027Q4	NA	4779.357

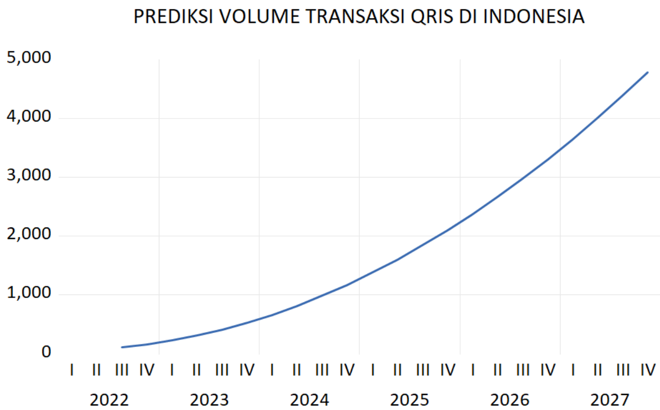


Figure 5: Prediction of QRIS transaction volume in Indonesia

Looking at the graph of the forecast results using the ARIMA (0,2,1) model shows that the volume of QRIS transactions in Indonesia will experience increasingly rapid growth throughout the period from 2022 to 2027. This model is estimated based on quarterly data, with the forecast period starting from the first quarter of 2022 to the fourth quarter of 2027. Visually, the projection curve shows a progressive upward trend, indicating an acceleration in the use of QRIS as a digital payment instrument in the national economy.

A comparison between actual data and forecast results shows that the ARIMA(0,2,1) model is able to follow the basic pattern of QRIS transaction volume growth, despite differences in values in several early periods. In the period (2022Q3–2024Q1), the forecast values were relatively close to the actual data, indicating that the model was able to capture the gradual upward trend. For example, in 2023Q1, the actual data was 125 million transactions, while the model predicted 226.14 million transactions. This difference indicates that the model tends to produce slightly higher estimates due to the very rapid growth pattern in the following period.

Entering the 2024 period, the correlation between actual data and predicted values is becoming increasingly apparent. In 2024Q3, actual data amounted to 619 million transactions, while the model predicted 987.07 million transactions. The ARIMA model captures the same trend direction, namely strong and consistent year-on-year growth. The predicted QRIS transaction volume of 4,779.357 trillion rupiah in 2027Q4 indicates a positive trend in Indonesia's digital economy transformation. This growth will contribute significantly to economic growth through increased consumption, empowerment of MSMEs, transaction efficiency, and expansion of financial inclusion.

These findings reinforce the results of research conducted by Rizka & Sendjaja (2025) that the use of QRIS provides tangible benefits for MSMEs, particularly in improving transaction convenience and overcoming previous payment obstacles. Although the payment system was already considered secure prior to the implementation of QRIS, this technology is able to maintain consistent security, thereby strengthening the confidence of MSME players. Additionally, QRIS has the potential to improve business performance through more efficient transaction processes and expanded access to digital markets. Overall, QRIS is an effective solution for enhancing efficiency, security, and economic growth for SMEs in the digital era. The implementation of QRIS in Indonesia has a positive impact on economic growth and the development of digital businesses through improved transaction efficiency, transparency, and access to services.

5 Conclusion

This study successfully developed a model for forecasting QRIS transaction volumes in Indonesia using the ARIMA (Box-Jenkins) method with quarterly data from Q1 2022 to Q2 2025. The analysis results show that the data reached stationarity after undergoing a second differencing process (d=2). Of the four candidate models tested, the ARIMA(0,2,1) model was selected as the best model based on the highest Adjusted R-Squared criterion (0.302543), lowest AIC (10.36322), and lowest SIC (10.48445). The model has passed all diagnostic tests, including residual normality, autocorrelation freedom, homoscedasticity, and system stability. The forecasting results show that QRIS transaction volume will experience very significant progressive growth from 1,841.5 trillion rupiah in Q3 2025 to 4,779.357 trillion rupiah in Q4 2027. This upward trend indicates that QRIS will become the dominant digital payment instrument, contributing to the acceleration of Indonesia's digital economic transformation, increased transaction efficiency, empowerment of MSMEs, and expansion of financial inclusion for the community.

Reference

ASPI. Statistik QRIS. https://aspi-indonesia.or.id/statistik-qris/

Ariyanto, F., & Tamam, M. B. (2020). Analisis Time Series Dengan Metode Arima Dan Aplikasinya. *Jurnal Aplikasi Teknologi Informasi Dan Manajemen (JATIM)*, *1*(2), 26–36. https://doi.org/10.31102/jatim.v1i2.972

Asrirawan, A., Permata, S. U., & Fauzan, M. I. (2022). Pendekatan Univariate Time Series Modelling untuk Prediksi Kuartalan Pertumbuhan Ekonomi Indonesia Pasca Vaksinasi COVID-19. *Jambura Journal of Mathematics*, *4*(1), 86–103. https://doi.org/10.34312/jjom.v4i1.11717

Atman Maulana, H. (2018). Pemodelan Deret Waktu Dan Peramalan Curah Hujan Pada Dua Belas Stasiun Di Bogor. *Jurnal Matematika, Statistika, Dan Komputasi*, *15*(1), 50–63.

Bank Indonesia. (2023). https://www.bi.go.id/id/publikasi/ruang-media/news-release/Pages/sp_2521123.aspx

Febiola, A., Dewi, A., Fazarin, F. M., Ramadhani, F., Khaffi, M. A., Akbar, R., & Dalimunthe, D. Y. (2024). Perbandingan Metode ARIMA dan SARIMA Dalam Peramalan Jumlah Penumpang Bandara Provinsi Kepulauan Bangka Belitung. *Jambura Journal of Mathematics*, *6*(2), 160–168. https://doi.org/10.37905/jjom.v6i2.25081

Hassyddiqy, H., & Hasdiana, H. (2023). Analisis Peramalan (Forecasting) Penjualan Dengan Metode ARIMA (Autoregressive Integrated Moving Average) Pada Huebee Indonesia. *Data Sciences Indonesia (DSI)*, *2*(2), 92–100. https://doi.org/10.47709/dsi.v2i2.2022

Muhammad Fahmuddin S, Ruliana Ruliana, S. S. M. M. (2023). Perbandingan Metode ARIMA dan Single Exponential Smoothingdalam Peramalan Nilai Ekspor Kakao Indonesia. *VARIANSI:Journal of Statistics and Its Application on Teaching and Research*, *5*(3), 163–176. https://jurnalvariansi.unm.ac.id/index.php/variansi/article/view/193

Nur Aisyah Indarningsih, & Hasbi. (2022). Analisis Perbandingan Risiko Volatilitas Indeks Harga Saham Syariah dan Konvensional (Jakarta Islamic Indeks dan Indeks LQ45). *Jurnal Ekonomi Syariah Teori Dan Terapan*, *9*(5), 694–709. https://doi.org/10.20473/vol9iss20225pp694-709

Rachman, A., Julianti, N., & Arkoyah, S. (2024). Challenges and Opportunities for QRIS

Implementation as a Digital Payment System in Indonesia. *EkBis: Jurnal Ekonomi Dan Bisnis, 8*(1), 1–13. https://doi.org/10.14421/ekbis.2024.8.1.2134

Rizka, I., & Sendjaja, T. (2025). Digitalisasi UMKM Pasca Pandemi: Evaluasi Kontribusi QRIS terhadap Pemulihan Ekonomi Rakyat. *Jurnal Ekonomika Dan Bisnis (JEBS)*, *5*(3), 628–633. https://doi.org/10.47233/jebs.v5i3.2907

Tan, E., & Astuti, I. (2020). Metode Autoregressive Integrated Moving Average untuk Meramalkan Penjualan. *EKOMABIS: Jurnal Ekonomi Manajemen Bisnis*, *1*(02), 149–158. https://doi.org/10.37366/ekomabis.v1i02.43

Yani, P. (2025). Dampak QRIS terhadap Kedaulatan Digital Indonesia dan Hubungan Perdagangan Internasional Response Code Indonesian Standard) adalah inovasi sistem pembayaran digital nasional yang dirilis oleh Bank Indonesia sebagai wujud nyata dari kedaulatan digital Ind. *Jurnal Bisnis, Ekonomi Syariah, Dan Pajak*, *2*(2), 36–44. https://doi.org/https://doi.org/10.61132/jbep.v2i2.1032

Yuliawanti, F. D., Novitasari, D. C. R., Widodo, N., Hamid, A., & Utami, W. D. (2021). Application of Autoregressive Integrated Moving Average (ARIMA) Method for Sunspot Number Prediction. *Barekeng*, *15*(3), 555–564. https://doi.org/10.30598/barekengvol15iss3pp555-564