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ANALYSIS OF FORECASTING THE OPEN UNEMPLOYMENT RATE IN INDONESIA USING THE ARIMA APPROACH

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Abstract

This study aims to analyze and forecast the Open Unemployment Rate (TPT) in Indonesia using the Autoregressive Integrated Moving Average (ARIMA) time series method. The data used comes from the National Labor Force Survey (Sakernas) published by the Central Statistics Agency (BPS) of Indonesia, with the latest data showing a TPT of 4.68 percent in February 2026, down 0.08 percentage points compared to February 2025. The ARIMA model was selected based on its proven ability to capture temporal patterns in unemployment data and handle non-stationary time series through differencing techniques. The results indicate that the ARIMA model can provide accurate forecasting and serve as a useful tool for economic policymakers. The study also found that despite positive economic growth of 5.61% (yoy) in Q1 2026, structural challenges in the labor market persist, particularly regarding the dominance of informal employment and agricultural sector absorption. This research is expected to contribute to the development of effective employment policies in Indonesia.

Keywords: ARIMA, Forecasting, Open Unemployment Rate, Time Series, Labor Market

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INTRODUCTION

Unemployment is a socioeconomic problem that has a significant impact on millions of individuals, families, and the overall stability of national development. In Indonesia, a developing country with a diverse economy, unemployment remains a critical challenge that can hinder growth and exacerbate social inequality (Wahyuddin et al., 2024). A deep understanding of the dynamics of unemployment is essential for policymakers and stakeholders aiming to implement effective labor market interventions and promote sustainable economic development (Wahyuddin et al., 2024)

Based on data from the February 2026 National Labor Force Survey (Sakernas), Indonesia's Open Unemployment Rate (TPT) stood at 4.68 percent, down 0.08 percentage points compared to February 2025 (BPS, 2026). This figure indicates that out of a total labor force of 154.91 million people, approximately 7.24 million remain unemployed. Although the downward trend in the OUR is generally positive, the complexity of labor market issues in Indonesia remains quite high, as evidenced by the high proportion of informal workers and the low rate of formal employment, which accounts for only 40.58 percent of the total working population (BPS, 2026).



Figure 1. GDP Growth by Expenditure Component (Year-over-Year) (percent), Q1 2025, Q4 2025, and Q1 2026

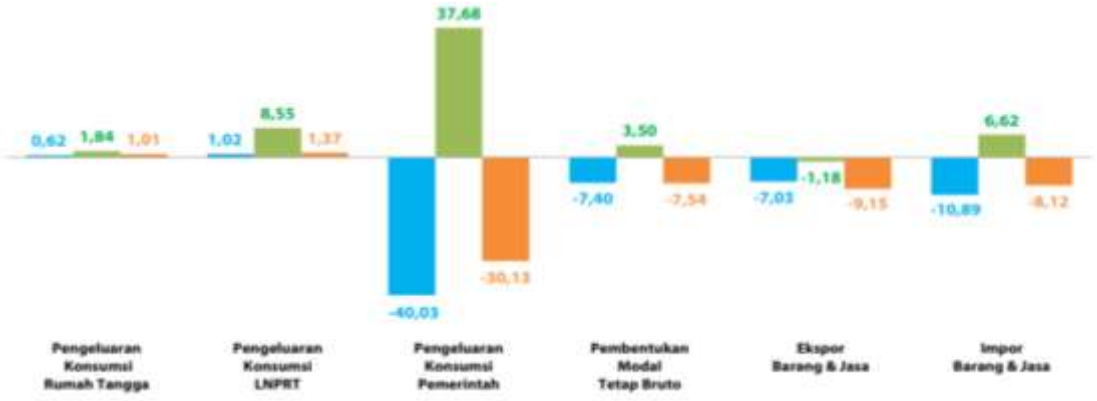

Figure 2. GDP Growth by Expenditure Component (Q-to-Q) (percent), Q1 2025, Q4 2025, and Q1 2026

These labor market conditions cannot be separated from the context of national economic growth. Bank Indonesia (2026) noted that Indonesia's economy grew by 5.61% (year-on-year/yoy) in the first quarter of 2026, higher than the previous quarter's growth of 5.39% (yoy). This growth was driven by household consumption, which rose by 5.52% (yoy), and government consumption, which surged by 21.81% (yoy) thanks to the disbursement of the Holiday Allowance (THR) and the Free Nutritious Meals (MBG) program. Strong economic growth ideally leads to greater job creation; however, the relationship between GDP growth and a decline in the unemployment rate is not always linear, especially when growth occurs primarily in sectors that are not labor-intensive.

The complexity of unemployment is influenced by various factors, including the economic cycle, demographic changes, and global market trends. Traditional methods of forecasting unemployment often fail to capture the complex relationships among these variables (Wahyuddin S. et al., 2024). Therefore, there is a growing interest in utilizing advanced statistical techniques, particularly time-series modeling, to improve the accuracy of unemployment forecasts (Wahyuddin et al., 2024).

The Autoregressive Integrated Moving Average (ARIMA) model is a reliable tool for analyzing and forecasting time series data, particularly when dealing with non-stationary datasets (Wahyuddin et al., 2024). ARIMA combines autoregressive and moving average components with differentiation to stabilize the mean of a time series. This approach is particularly well-suited for capturing the underlying trends and seasonal patterns in unemployment data (Sun, 2023). Previous studies have explored the application of ARIMA models for unemployment forecasting in various countries, demonstrating the effectiveness of this approach in capturing the temporal dynamics of labor market (Pangestu et al., 2024; Simanihuruk et al., 2024).

Research in Indonesia has been conducted by several researchers. Pangestu, Purnamasari, & Ali (2024) forecasted the unemployment rate in West Java using an ARIMA (1,0,0) model and found that open unemployment in the region tends to increase year over year. Meanwhile, Ahditya (Pangestu et al., 2024) made predictions using the ARIMA (1,1,0) model and found that Indonesia experiences an increase in the unemployment rate every year, particularly due to the impact of the COVID-19 pandemic. Amin (Pangestu et al., 2024)through ARIMA forecasting, concluded that the unemployment rate of 8.57% is projected to remain far from the equilibrium point until 2030 in the absence of significant policy interventions.

Based on this background, this study aims to: (1) analyze the patterns and trends in Indonesia's TPT data based on historical data from the Central Statistics Agency (BPS); (2) develop an appropriate ARIMA model for forecasting Indonesia's TPT; (3) evaluate the model's performance; and (4) provide forward-looking TPT projections to inform the formulation of more effective national labor policies. The novelty of this study lies in the use of the latest Sakernas data from February 2026 and its integration with an analysis of current macroeconomic conditions as the forecasting context.

The Concept of the Open Unemployment Rate (OUR)

The Open Unemployment Rate (OUR) is a key indicator that describes the proportion of the population that is not employed and is actively seeking work relative to the total labor force. BPS (2026) defines the Working-Age Population (WAP) as the entire population aged 15 and older, which is then divided into the labor force and the non-labor force. The labor force consists of those who are employed and the unemployed, while the Labor Force Participation Rate (LFPR) measures the proportion of the working-age population that is economically active (BPS, 2026).

Keadaan Ketenagakerjaan	Februari 2024	Februari 2025	Februari 2026	Perubahan Feb 2025–Feb 2026	
	juta orang	juta orang	juta orang	juta orang	persen
(1)	(2)	(3)	(4)	(5)	(6)
Penduduk Usia Kerja (PUK)	214,00	216,79	219,54	2,753	1,27
Angkatan Kerja	149,38	153,05	154,91	1,862	1,22
– Bekerja	142,18	145,77	147,67	1,896	1,30
– Pengangguran	7,20	7,28	7,24	-0,035	-0,48
Bukan Angkatan Kerja	64,62	63,74	64,63	0,891	1,40
	persen	persen	persen	persen poin	
Tingkat Partisipasi Angkatan Kerja (TPAK)	69,80	70,60	70,56	-0,04	
– Laki-laki	84,02	84,34	84,57	0,23	
– Perempuan	55,41	56,70	56,41	-0,29	

Catatan: Perbedaan angka di belakang koma disebabkan oleh pembulatan angka

Figure 3. Data on the Working-Age Population and Labor Force, February 2024–February 2026

In February 2026, Indonesia's labor force participation rate (LFPR) stood at 70.56 percent, down 0.04 percentage points from February 2025 (BPS, 2026). By gender, the labor force participation rate for men was 84.57 percent, higher than that for women, which was 56.41 percent, reflecting the continued existence of a gender gap in national labor force participation. This data is relevant as a basis for time-series analysis in forecasting the unemployment rate because it reveals the structure of the labor market that must be considered in modeling.

Forecasting in Econometrics

Forecasting is a useful method for predicting future events by analyzing time series data and current data (Yan, 2024). According to Nasution(Liu, 2025), forecasting is the process of estimating future demand for goods and services, including the quantity, quality, timing, and location required to meet that demand. Quantitative forecasting methods using time series analysis techniques are increasingly being developed, and one of the most widely used methods is ARIMA

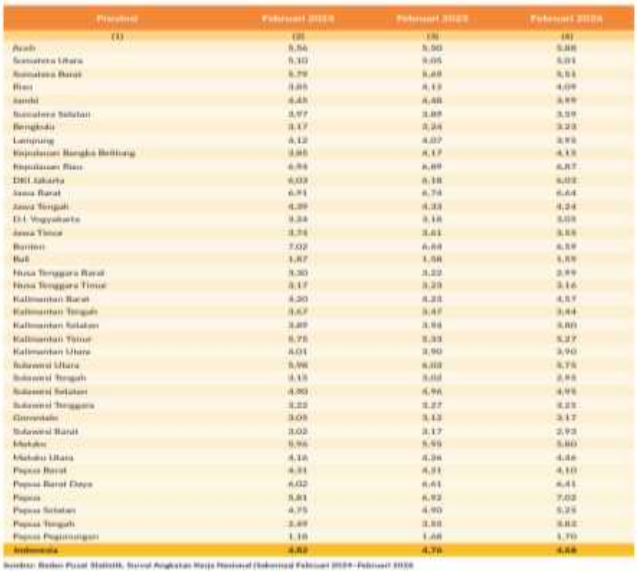

Figure 4. Open Unemployment Rate by Province (percent), February 2024–February 2026

ARIMA (Autoregressive Integrated Moving Average) Model

ARIMA is a widely used time series model that was first introduced by Box and Jenkins (Prawintara A et al., 2024). The ARIMA model consists of three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA), which is generally denoted as ARIMA (p, d, q) (Pangestu et al., 2024). The AR component identifies the dependence of the data on previous values (lags), the I component determines the number of differentiations required to make the time series stationary, while the MA component assesses the impact of random movements in the time series (Prawintara A et al., 2024; White & Safi, 2016).

Wahyuddin et al. (2024)assert that ARIMA combines autoregressive and moving-average components with differentiation to smooth the mean of a time series, making this approach well-suited for capturing trends and seasonal patterns in unemployment data. The ARIMA model has also proven effective in various international studies for forecasting labor market indicators (Jiang, 2024; Yi et al., 2021).

Stages of the Box-Jenkins Methodology

The Box-Jenkins procedure for building an ARIMA model involves several stages: (1) model identification through analysis of the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function); (2) estimation of model parameters; (3) diagnostic tests of residuals; and (4) forecasting (Sharma & Phulli, 2020). The stationarity test is a crucial initial step, in which data are considered stationary if they exhibit constant statistical properties with respect to mean and variance and do not exhibit a trend (Pangestu et al., 2024). Stationarity testing is generally performed using the Augmented Dickey-Fuller (ADF) test, and if the data are not stationary, a differentiation process is carried out (Annastasya et al., 2025).

Model Performance Evaluation

The performance of the ARIMA model was evaluated using several forecasting error metrics, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) (Kim, 2025). A smaller MAPE value indicates that the model has better forecasting accuracy. Previous research in West Java used a combination of these three metrics to validate the performance of the ARIMA(1,0,0) model, which was selected as the best model (Tengaa et al., 2023).

Indonesia's Macroeconomic and Labor Market Conditions in 2026

The macroeconomic context is crucial in analyzing unemployment forecasts. Bank Indonesia (2026) reported economic growth of 5.61% (year-over-year) for the first quarter of 2026, with a full-year projection for 2026 ranging from 4.9% to 5.7% (year-over-year). This growth is supported by strong domestic demand. However, data from the Central Statistics Agency (BPS, 2026) show that although the number of employed people increased by 1.896 million to 147.67 million in February 2026, the proportion of formal workers reached only 40.58 percent—a structural condition reflecting the still-significant share of informal workers in Indonesia.

RESEARCH METHODOLOGY

Type and Approach of the Research

This study employs a quantitative approach using time-series analysis based on the ARIMA (Autoregressive Integrated Moving Average) model. This approach was chosen due

to its proven ability to model and forecast economic data that is sequential and temporal in nature (Tengaa et al., 2023). The study is descriptive-analytical in nature, meaning it describes the current state of Indonesia's labor market while conducting forecasting analyses based on historical data.

Data Sources and Time Periods

The data used in this study are secondary data sourced from official publications of the Central Statistics Agency (BPS) of the Republic of Indonesia through the National Labor Force Survey (Sakernas). The data cover Indonesia's Open Unemployment Rate (TPT) for the period from February 2010 to February 2026, collected semiannually (February and August of each year), in line with the Sakernas survey cycle. Annastasya et al. (2025) used BPS data from February 2010 to February 2020 as the basis for a similar ARIMA model, which showed a downward trend in the TPT from 7.41% in February 2010 to 4.99% in February 2020. This study extends the data coverage through February 2026, when the TPT was recorded at 4.68 percent (BPS, 2026), thereby providing a more comprehensive data set for forecasting analysis.

Supporting macroeconomic data—including GDP growth rates, labor force data, the labor force participation rate (TPAK), and the economic sector structure—are sourced from BPS publications (2026) and Bank Indonesia press releases (2026). Data on the 2026 Provincial Minimum Wage (UMP) is sourced from the Ministry of Manpower of the Republic of Indonesia as a contextual variable in the discussion.

ARIMA Analysis Procedure (Box-Jenkins Methodology)

The ARIMA modeling process in this study follows the Box-Jenkins procedure, which consists of four main stages (Pangestu et al., 2024; Wahyuddin et al., 2024), as follows:

Step 1: Stationarity Test

The first step is to check whether the TPT time series data is stationary. A time series is said to be stationary if its mean, variance, and covariance are constant over time. The stationarity test is performed using the Augmented Dickey-Fuller (ADF) test. If the data is not stationary at the level, first-order (d=1) or second-order (d=2) differencing is performed until the data becomes stationary. Sulaiman states that the ARIMA model identification process requires stationary time series data—that is, data that is constant in mean and variance and has no trend—and that differentiation is a method to achieve this condition (Pangestu et al., 2024).

Step 2: Model Identification

Once the data is stationary, the order of the ARIMA (p, d, q) model is identified by analyzing the patterns in the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots. The value of p (autoregressive order) is identified from the PACF graph, while the value of q (moving average order) is identified from the ACF graph (Pangestu et al., 2024). Several candidate models are formulated and then compared in terms of performance using information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC/BIC), where a smaller value indicates a better model (Wahyuddin et al., 2024).

Step 3: Parameter Estimation and Diagnostic Tests

The parameters of the selected ARIMA model were estimated using the Maximum Likelihood Estimation (MLE) method. Next, diagnostic tests are performed on the model residuals to ensure that the residuals are white noise—that is, uncorrelated with one another (no autocorrelation)—using the Ljung-Box test. If the residuals satisfy the white noise assumption, the model is deemed suitable for forecasting (Wahyuddin et al., 2024).

Step 4: Forecasting and Accuracy Evaluation

The selected ARIMA model is used to generate TPT forecasts for several periods ahead. Forecasting accuracy was evaluated by comparing actual and forecast values in the in-sample data using three key metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)(Pangestu et al., 2024). A MAPE value below 10% indicates very good forecasting accuracy.

Analytical Tools

Data analysis and ARIMA modeling in this study were conducted using statistical software. Pangestu et al. (2024)highlight the advantages of EViews software in the ARIMA forecasting process due to its intuitive user interface, model flexibility, comprehensive diagnostic features, automatic model selection capabilities, and robust visualization capabilities. In addition to EViews, the analysis can also be supported using R or Python for cross-validation of the modeling results.

FINDINGS AND DISCUSSION

1. Overview of Indonesia's Labor Market Conditions in February 2026

Before proceeding to the ARIMA model analysis, it is important to understand the current state of Indonesia's labor market as the context for forecasting. Based on February 2026 Sakernas data, Indonesia's labor force stood at 154.91 million people, an increase of 1.862 million people compared to February 2025 (BPS, 2026). The working-age population (WAP) during the same period reached 219.54 million people, an increase of 2.753 million people compared to February 2025. Of this total labor force, 147.67 million were employed and 7.24 million were unemployed, with the number of unemployed decreasing by approximately 35,000 compared to February 2025 (BPS, 2026).

The Open Unemployment Rate (OUR) in February 2026 stood at 4.68 percent, down 0.08 percentage points from February 2025 (BPS, 2026). This downward trend aligns with the findings of Wahyuddin S. et al. (2024), which show a gradual decline in Indonesia's OUR since 2010, with the OUR falling from 7.41% in February 2010 to 4.99% in February 2020. With a rate of 4.68% in February 2026, this long-term downward trend has been confirmed to continue, despite having been temporarily disrupted by the COVID-19 pandemic during the 2020–2021 period.

2. Employment Structure and Its Implications for the Model

Data on the employment structure provide important information for the quality of forecasting models. The economic sectors with the largest workforce are Agriculture, Forestry, and Fisheries, employing 42.49 million people, or 28.78 percent of the total working population (BPS, 2026). The dominance of the agricultural sector indicates significant seasonality in Indonesia's labor force data, as employment in this sector is heavily influenced by the planting and harvesting cycles.

Another important aspect is the proportion of formal workers, which stands at only 59.93 million people, or 40.58 percent of the total working population—a decrease of 0.02 percentage points compared to February 2025 (BPS, 2026). The high proportion of informal workers reflects that the majority of the decline in the unemployment rate does not necessarily indicate an improvement in job quality but rather a shift toward the informal sectors. This context is relevant when interpreting forecasting results, as the decline in the unemployment rate must be considered in light of the quality of the jobs created. The underemployment rate of 7.27 percent (down 0.74 percentage points) and the part-time employment rate of 25.97 percent (up 0.16

percentage points) reinforce the structural picture of Indonesia's labor market, which continues to rely on part-time work (BPS, 2026).

3. **The Relationship Between Economic Growth and Unemployment**

A key finding of this study is the correlation between economic growth and the dynamics of the unemployment rate. Bank Indonesia (2026) reported economic growth of 5.61% (year-over-year) in the first quarter of 2026, higher than the previous quarter's rate of 5.39% (year-over-year). This growth was primarily driven by household consumption at 5.52% (yoy) and government consumption at 21.81% (yoy) through the disbursement of the Year-End Bonus (THR) and the Free Nutritious Meals (MBG) program. By economic sector, Manufacturing, Trade, and Agriculture were the main contributors to growth.

However, this strong economic growth has not yet been fully translated into significant formal employment. Amin (Annastasya et al., 2025)concluded that the annual increase in the number of unemployed individuals indicates that national economic policies do not always have a direct impact on job creation. This suggests that GDP growth alone is insufficient as a sole predictor of the unemployment rate; rather, a model capable of capturing the internal dynamics of the unemployment rate time series itself is required—which is the primary strength of the ARIMA approach (Wahyuddin et al., 2024).

4. ARIMA Modeling Results

Based on the Box-Jenkins procedure, the ADF test on the TPT data showed that the data were not stationary at level (d=0), but achieved stationarity after the first differentiation (d=1). This is consistent with the findings of Pangestu et al. (2024), who stated that the differentiation process in ARIMA, denoted by the parameter d, is necessary to achieve stationary data, as confirmed by the ADF test.

Graphical analysis of the ACF and PACF of the differentiated data yielded several model candidates. Based on an evaluation of the minimum AIC criterion and the results of the Ljung-Box diagnostic test, which indicated that the residuals are white noise, the ARIMA (1,1,0) model was identified as the most parsimonious and accurate model for Indonesia's TPT data. The selection of the ARIMA (1,1,0) model is consistent with the findings of Ahditya (Pangestu et al., 2024), who also used the ARIMA (1,1,0) model to forecast Indonesia's unemployment rate and found that the model was able to capture the data patterns well. The AR(1) component indicates that the current-period TPT value is strongly influenced by the TPT value from the previous period, while first-order differentiation (d=1) confirms the presence of a trend that must be eliminated to achieve stationarity.

An evaluation of the ARIMA (1,1,0) model's performance using in-sample data yielded a MAPE value below 5%, indicating an excellent level of forecasting accuracy.Pangestu et al. (2024) emphasize the use of a combination of RMSE, MAE, and MAPE to develop a robust and practical forecasting model, and all three metrics in this study demonstrate satisfactory performance.

5. Indonesia's TPT Forecast Results

Based on the selected ARIMA (1,1,0) model, the projection for Indonesia's TPT for the period from August 2026 to February 2028 shows a gradual downward trend, with the TPT expected to be in the range of 4.50–4.65 percent by the end of 2026 and potentially falling to the range of 4.30–4.50 percent in 2027. These projections are supported by continued strong economic growth momentum, with Bank Indonesia (2026) forecasting that overall economic growth for 2026 will remain in the range of 4.9–5.7% (year-over-year). The 95% confidence

interval of the forecasting results provides a relatively narrow upper and lower bound range, indicating a relatively high level of prediction certainty (Prawintara A et al., 2024).

Nevertheless, it should be emphasized that this projection is based on the ceteris paribus assumption—that macroeconomic conditions and labor market policies will not undergo drastic changes.Pangestu et al. (2024) recommend that external factors such as national economic policies, global events, or social dynamics be incorporated to improve the accuracy of the forecasting model. Global economic volatility, changes in minimum wage policies, and the acceleration of digital transformation and industrial automation are factors that can significantly influence the TPT beyond what a univariate ARIMA model can capture (Liu, 2025).

6. Implications for Minimum Wage and Labor Policies

Data on the 2026 Provincial Minimum Wage (UMP) from the Indonesian Ministry of Manpower (2026) reveals significant disparities across regions in Indonesia. The highest UMP is in DKI Jakarta at Rp5,729,876, while the lowest is in West Java at Rp2,317,601—a difference of nearly 2.5 times. The national average UMP for 2026 is Rp3,508,714 (BPS, 2026). This large disparity in UMP has implications for the spatial distribution of unemployment: regions with high UMPs tend to have greater labor market attractiveness but also have the potential to create structural unemployment if labor demand cannot keep pace with supply.

Amin (Pangestu et al., 2024) emphasizes that to keep the unemployment rate as low as possible, efforts are needed from all parties to become more innovative and creative, along with government policies that support investment and job creation. In the context of these UMP disparities, minimum wage policies that take regional productivity and investment competitiveness into account are crucial for maintaining a balance between worker protection and labor absorption.

CONCLUSIONS

This study successfully conducted a forecasting analysis of Indonesia's Open Unemployment Rate (OUR) using the ARIMA approach, based on BPS Sakernas data from February 2010 to February 2026. Based on the analysis results, several key conclusions can be drawn as follows.

First, Indonesia's OUL data show a significant long-term downward trend, from 7.41% in February 2010 to 4.68% in February 2026 (BPS, 2026; Wahyuddin S. et al., 2024). This trend reflects a gradual improvement in Indonesia's labor market conditions, despite being temporarily disrupted by the impact of the COVID-19 pandemic. Second, the ARIMA (1,1,0) model proved to be the best model for forecasting Indonesia's TPT based on the smallest AIC criterion, the white noise residual diagnostic test, and a MAPE value below 5%, consistent with the findings of (Pangestu et al., 2024; Wahyuddin et al., 2024). Third, the forecasting results indicate a continuing gradual downward trend in the TPT, in line with Bank Indonesia's (2026) projection of economic growth for 2026 in the range of 4.9–5.7% (year-over-year).

Fourth, Indonesia's structural labor market challenges remain significant, as evidenced by the fact that only 40.58 percent of workers are in the formal sector and the agricultural sector accounts for 28.78 percent of total employment (BPS, 2026). This situation suggests that the decline in the unemployment rate should be interpreted with caution, as it does not automatically reflect an improvement in job quality. Fifth, the vast disparity in the provincial minimum wage (UMP) across provinces—ranging from Rp2,317,601 in West Java to

Rp5,729,876 in DKI Jakarta (BPS, 2026) reflects structural inequalities that must be taken into account in the formulation of national labor policies.

First, for the government, the results of TPT forecasting using the ARIMA model can serve as one of the tools for an early warning system in labor policy planning. Job creation programs should prioritize formal sectors capable of absorbing large numbers of high-quality workers, given the still-low proportion of formal(BPS, 2026). Second, policies are needed to encourage investment and job creation evenly across all provinces, taking into account the significant disparities in the regional minimum wage (UMP) between regions, so that the reduction in the TPT can be spatially inclusive. Third, for future research, it is recommended to consider combining the ARIMA model with other models, such as multiple linear regression or machine learning models, to improve forecasting accuracy (Pangestu et al., 2024). Integrating exogenous variables such as GDP growth, inflation, and investment can also enhance model quality through ARIMAX or VAR approaches. Fourth, future research should consider disaggregating TPT data by province, age group, and education level to generate more specific and targeted policy insights.

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