Volume: 11 Issues: 88 Special Issue [November, 2026] pp 1066-1078
Journal of Islamic, Social, Economics and Development (JISED)
eISSN: 0128-1755
Journal website: academicinspired.com/jised
DOI: 10.55573/JISED.118873

FORECASTING BIRTH RATES IN MALAYSIA: AN AUTOREGRESSIVE INTEGRATED MOVING AVERAGE APPROACH

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Article history
Received date : 12-10-2026
Revised date : 13-10-2026
Accepted date : 16-11-2026
Published date : 17-11-2026

To cite this document:
Abdul Razak, M. F. H., Norshahidi, N. D., & Wan Husin, W. Z. (2026). Forecasting birth rates in Malaysia: An autoregressive integrated moving average approach. *Journal of Islamic, Social, Economics and Development (JISED),* 11 (88), 1066-1078.

Abstract: *Crude birth rate (CBR) is an important demographic indicator with major implications for economic development, healthcare planning, and policymaking. The main aim of this study is forecasting Malaysia' CBR. It applies the Autoregressive Integrated Moving Average (ARIMA) model in analysing historical birth rate data from 2000 to 2023 obtained from the Department of Statistics Malaysia (DOSM). The results show a clear downward trend in Malaysia's CBR which consistent with global demographic patterns and raising concerns about the long-term socio-economic impacts of an ageing population. Among the models tested, ARIMA (1,1,2) was identified as the most appropriate, achieving the best AIC and BIC values for in-sample evaluation, as well as the lowest RMSE, MAE, and MAPE for out-of-sample forecast accuracy. Forecasts generated indicate that the CBR is expected to continue declining over the next seven years (2024 to 2030). Overall, this study highlights the value of time series forecasting as a practical tool for supporting national planning and suggests that future research could improve predictive performance by incorporating additional explanatory variables or adopting hybrid modelling approaches.*

Keywords: *ARIMA*, *Crude birth rate*, *Fertility rate*, *Demography*, *Forecasting*.

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Introduction

Malaysia has experienced a considerable decline in its birth rate in recent years, reflecting a broader demographic trend observed in both developed and developing countries. For instance, the number of live births in Malaysia decreased by 10.2% to 100,732 in the second quarter of 2024 compared with the corresponding period in the previous year (Ghazali, 2024). This declining trend has important implications for the country's future demographic and economic development. Several factors have been associated with this pattern, including rising living costs, increasing educational attainment among women, delayed marriages, and the growing financial responsibilities of raising children (Amirul Ihsan, 2024). At the global level, the average fertility rate declined substantially from 5.0 children per woman in 1960 to 2.3 in 2021, with an increasing number of countries reporting fertility rates below the replacement level (Dattani et al., 2023; World Bank, 2023; Our World in Data, 2023). Despite various government initiatives to encourage higher fertility, countries such as South Korea, Japan, and several European nations continue to experience fertility rates below the replacement threshold of 2.1 children per woman (Organisation for Economic Co-operation and Development [OECD], 2024). This demographic transition has raised concerns about population ageing, a shrinking labour force, and increasing pressure on social protection systems. As fewer young people enter the workforce, countries may face labour shortages that could affect key economic sectors and constrain productivity. Therefore, understanding changes in birth patterns through reliable forecasting is increasingly important. Such projections can assist governments in planning future employment needs, healthcare services for ageing populations, and the provision of educational facilities. In this regard, Tanmoy et al. (2024) emphasised the importance of reliable demographic forecasting in helping governments formulate policies that respond effectively to changing population dynamics and emerging economic challenges.

The situation in Malaysia further highlights the importance of addressing this demographic concern. According to Uzir (2024), the national Total Fertility Rate (TFR) had declined to approximately 1.6 children per woman, with Penang and Kuala Lumpur recording particularly low rates of 1.2 children per woman. In response to declining fertility, policymakers have introduced various initiatives, including increased childcare assistance and tax incentives to support working mothers and encourage female labour force participation (Amirul Ihsan, 2024). Nevertheless, the continued decline in birth rates highlights the need for more reliable demographic projections to support long-term planning and evidence-based policymaking. Accurate birth-rate forecasts are important for effective resource allocation, workforce planning, and the development of policies that address future demographic and economic challenges (Tanmoy et al., 2024). Birth trends also have direct implications for national planning in areas such as public health, education, housing, and employment (United Nations, 2019; World Health Organization, 2020). From a sustainable development perspective, demographic forecasting can further support the monitoring of progress towards the United Nations Sustainable Development Goals (SDGs), particularly those related to health, education, gender equality, and economic growth (United Nations Development Programme, 2026).

Given these implications, considerable attention has been directed towards developing appropriate statistical methods for demographic forecasting (Bohk-Ewald et al., 2018; Booth, 2006). In general, forecasting approaches can be classified into demographic models, conventional statistical time-series models, and machine-learning techniques (Booth, 2006). Demographic approaches, including cohort-component models, Lee-Carter extensions, and Age-Specific Fertility Rate (ASFR) models, provide detailed information on fertility patterns across different age groups and population characteristics (Lee & Carter, 1992; Shair et al.,

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2024a; Ševčíková et al., 2011). Functional data models have also been widely applied to examine smooth variations and structural shifts in fertility curves across demographic groups (Hyndman & Ullah, 2007; Shair et al., 2024b). Although these structural and functional approaches offer rich insights into disaggregated population dynamics, they generally require detailed age-stratified demographic registries and complex multi-parameter specifications (Booth, 2006; Hyndman & Ullah, 2007). Consequently, their application is often less straightforward and vulnerable to parameter uncertainty when the main objective is to forecast an aggregate demographic indicator using a relatively short historical series (Lian & Hamdan, 2024; Shitan & Ng, 2015).

Machine-learning methods, such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks, have also been explored in time-series and fertility rate forecasting because of their ability to capture nonlinear relationships and complex temporal patterns (Nyoni et al., 2021; Perla et al., 2021). However, their performance depends considerably on the availability of sufficient training observations and appropriate hyperparameter configurations (Cerqueira et al., 2022; Makridakis et al., 2018). When applied to annual demographic data with a limited number of observations, highly parameterised models are particularly susceptible to overfitting, which can compromise out-of-sample forecast accuracy and reliability (Hyndman & Athanasopoulos, 2021; Makridakis et al., 2018). Furthermore, the architectural complexity of these approaches often reduces model transparency, making their predictive behavior more difficult to interpret for policy formulation (Hyndman & Athanasopoulos, 2021; Rudin, 2019). Therefore, the selection of an appropriate forecasting method should carefully consider the availability of the data and the interpretability required of the resulting model (Box et al., 2015; Hyndman & Athanasopoulos, 2021).

Among conventional statistical forecasting approaches the ARIMA model is particularly recognised for its effectiveness in univariate time-series analysis (Lian & Hamdan, 2024). The model combines autoregressive and moving-average components with differencing procedures to account for temporal dependence and non-stationarity in the observed series (Box et al., 2015). Unlike approaches that require extensive explanatory variables or detailed demographic classifications, ARIMA primarily uses the historical observations of the variable of interest (Lian & Hamdan, 2024). This characteristic makes it relevant for forecasting aggregate demographic indicators, particularly when annual data are available over a relatively limited period. Its parsimonious structure also allows the model to be estimated using a manageable number of parameters, reducing the risk of unnecessary model complexity compared to multi-equation econometric or vector autoregressive specifications (Hyndman & Athanasopoulos, 2021; Nwokike, 2020). These characteristics provide a reasonable basis for considering ARIMA as a suitable forecasting approach for the present study, although its actual performance needs to be established empirically.

Previous studies have demonstrated the application of statistical time-series models in forecasting birth rates and other demographic indicators. In Malaysia, Shitan and Ng (2015) investigated birth-rate forecasting using ARIMA and alternative time-series approaches, including ARAR model. Subsequent studies have continued to explore the suitability of statistical forecasting techniques for Malaysian demographic data. Shair et al. (2024b) examined fertility patterns using demographic modelling approaches, while Lian and Hamdan (2024) and Soh (2024) investigated the application of statistical time-series methods to Malaysian birth-rate forecasting. Internationally, ARIMA based approaches have also been employed to forecast demographic trends (Zhang et al., 2024). These studies demonstrate the

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continued relevance of statistical models in analysing and forecasting demographic indicators. However, differences in the study periods, demographic measures, model specifications, and evaluation procedures mean that their findings may not necessarily reflect the current demographic conditions in Malaysia.

Despite these previous contributions, further investigation is warranted into the forecasting performance of ARIMA models using more recent Malaysian birth-rate data. Earlier studies, such as Shitan and Ng (2015), were conducted before Malaysia's more recent transition towards below-replacement fertility. Consequently, the models developed in those studies may require reassessment considering the country's changing demographic patterns. Although more recent research has examined Malaysian birth-rate trends, there remains a need for further empirical evaluation of updated ARIMA specifications, particularly through systematic residual diagnostic testing and short-term out-of-sample forecasting assessment. This distinction is important because a model that provides a satisfactory fit to historical observations does not necessarily produce reliable forecasts for future periods (Hyndman & Athanasopoulos, 2021). An updated and empirically validated ARIMA model would offer a useful statistical reference for understanding recent birth-rate developments and supporting short-term demographic planning in Malaysia.

In demographic research, the Crude Birth Rate (CBR) and Total Fertility Rate (TFR) are two commonly used indicators for examining fertility and population trends (Preston et al., 2001). Although both indicators provide valuable information about demographic changes, they measure different aspects of population dynamics. The TFR represents the average number of children a woman would have during her reproductive years based on prevailing age-specific fertility rates, whereas the CBR measures the number of live births per 1,000 population in a given year. This study focuses on CBR forecasting because it provides an aggregate measure of annual birth patterns and is particularly relevant for short- to medium-term planning. As discussed by Preston et al. (2001), birth-rate information is useful for anticipating changes in population size and planning public services, particularly maternal and child healthcare and educational facilities.

In view of these considerations, this study aims to develop and evaluate an appropriate ARIMA model for forecasting Malaysia's CBR. Specifically, the study examines the historical characteristics of the birth-rate series, identifies a suitable ARIMA specification, assesses model adequacy through diagnostic procedures, and evaluates its short-term forecasting performance using out-of-sample observations. By using updated demographic observations and assessing both model adequacy and out-of-sample forecasting performance, this study seeks to provide a relevant and transparent statistical baseline for projecting Malaysia's birth rate. The findings are expected to contribute to evidence-based demographic planning, particularly in anticipating changes in future population requirements and supporting the development of appropriate socioeconomic policies. More broadly, reliable demographic projections can contribute to national development priorities associated with the United Nations Sustainable Development Goals (SDGs), particularly Good Health and Well-being (SDG 3) and Decent Work and Economic Growth (SDG 8) (United Nations Development Programme, 2026).

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Methodology

Data Description

This study applies the ARIMA model to forecast Malaysia's CBR, with the aim of examining historical trends and providing insights into future demographic patterns. The analysis uses annual CBR data, expressed as the number of births per 1,000 population, covering the period from 2000 to 2023. The data were obtained from the Department of Statistics Malaysia (Department of Statistics Malaysia, 2024). The study period was selected based on the availability of consistent and comparable annual data at the time the research was conducted. Although the relatively short time series limits the number of available observations, the study focuses on this period to ensure data consistency throughout the analysis.

The dataset was divided into training and testing subsets using a 70:30 ratio to evaluate the forecasting performance of the ARIMA model. The first 70% of the observations, covering 2000 to 2016, were used for model estimation, while the remaining 30%, covering 2017 to 2023, were reserved for out-of-sample forecasting evaluation. This approach allows the predictive performance of the selected ARIMA model to be assessed using observations that were not included in the model estimation process.

Descriptive Statistics

Descriptive analysis was used in identifying the component of time series in CBR series. The CBR series may have both a trend and an irregular component because the data were gathered annually. A time series plot was employed to investigate the pattern of birth rate by years. To better understand the historical pattern of the birth rate data, the researchers employed trend analysis. This would make it easier to identify whether the trend of birth rate in Malysia is decreasing or increasing.

Autoregressive Integrated Moving Average Model

Autoregressive Integrated Moving Average (ARIMA) model is one of the most popular methods in time series forecasting. It is one of the methods formulated based on the Box–Jenkins methodology to predict observations with the help of several lagged time series data. An ARIMA model is a combination of the autoregressive (AR) component, the integrated (I) component, and the moving average (MA) component denoted as ARIMA (*p, d, q*) model. The notation p in the model represents the number of lagged observations in the AR component, denoted as AR (p), while q represents the number of lagged forecast error terms in the MA component, denoted as MA(q). Equation 1 shows the normal form of the pth ordered AR process in the study with p is the lag term of the birth rate variables. The observations at various slots t -1, t -2 and t -3, …, t -p influence the time period at t. The Autoregressive (AR) Model of order p is given in Equation 1 (Shetty, 2020) with y_t represent the CBR observation, μ is constant terms, $\phi_j (j = 1,2, \dots, p)$ is the estimated parameters,y_{t-p} is the p^{th} order of the lagged CBR and ε_t is the error term, which is assumed *iid* with mean zero and variance, σ_ε^2 (Shetty, 2020).

$$y_t = \mu + \phi y_{t-1} + \phi y_{t-2} + \cdots + \phi y_{t-p} + \varepsilon_t \quad (1)$$

The Moving Average (MA) model relates the current value of a CBR series to past random errors rather than to previous observations of the series itself. Consequently, the value of the CBR series at time t is influenced by random shocks that occur in previous periods, from $t-1$to $t-q$. As shown in Equation 2, the highest-order term denoted by q is the number of lagged

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DOI: 10.55573/JISED.118873

error terms included in the model. This is random shocks that capture unexpected external influences affecting the series. The MA coefficients determine the magnitude and direction of the impact of these past errors on the current observation (Shetty, 2020). The MA model of order q, denoted as MA(q) (Equation 2) is express with μ which is the mean about which the series fluctuates, $\theta's$, the estimated moving average parameters, and $\varepsilon_{t-q}'s$, the error terms (q=1,2,3,…) which assumed to be independently distributed over time (Shetty, 2020).

$$y_t = \mu - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} + \varepsilon_t \quad (2)$$

Consequently, the Autoregressive Moving Average (ARMA) model is strictly a combination of the AR(p) and MA(q) models (Shetty, 2020). The basic concept of ARMA model is that the data series should be stationarity, in which the mean and variance of the series are constant through time and not involved in any transformation. To forecast future values, this model accounts for both the residual errors and the effects of past time lags. As explained by Lazim (2013), the ARMA(p, q) model is mathematically expressed as:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} + \varepsilon_t \quad (3)$$

where definition of the parameters in the model and assumptions is similar with AR(p) and MA(q) model. However, when stationarity assumption is not met, the data series are transformed using differencing and the model becomes an ARIMA model with the I being integrated which represents the level of differencing Lazim (2013). The ARIMA model is expressed as ARIMA(p,d,q) where p and q is the order of the AR and MA model respectively and *'d'* is the level of non-seasonal needed for stationarity of the series.

Box-Jenkins methodology was used in analysing the ARIMA model. The methodology consists of three stages which are model identification, model estimation, and diagnostic checking of the model. In the model identification stage, data stationarity is verified using the visual spikes in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots and the Augmented Dickey-Fuller (ADF) test. and the spike in ACF and PACF are also analysed in identifying the level of differencing (d), the order of p for AR component and level o q for MA component. Next, in the estimation stage involved estimating the model parameters using Maximum Likelihood Estimation (MLE) and selecting the most parsimonious model configuration based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores. Finally, the diagnostic checking stage ensures model adequacy by subjecting the residuals to the Ljung-Box Q test. The model is deemed robust for forecasting if the residuals behave as white noise, whereas any remaining serial correlation requires returning to the first stage to evaluate alternative model specifications.

Model Estimation and Evaluation

In evaluating forecasting accuracy, a 70:30 train-test split was utilized to divide the dataset into two distinct subsets (Kavalci & Hartshorn, 2023). Each candidate ARIMA model was estimated using the in-sample training dataset, which comprised the first 70% of the time series data spanning the years 2000 to 2016. The evaluation of the in-sample fitted ARIMA models' performance was conducted using the AIC and the BIC, where lower AIC and BIC values indicate a more efficient and well-fitted model. The remaining 30% of the data, covering the years 2017 to 2023, served as the out-of-sample test dataset to generate out-of-sample forecasts. Evaluating the deviations between these out-of-sample forecasts and the actual values enabled the calculation of key forecast error metrics such as Root Mean Square Error (RMSE), Mean

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eISSN: 0128-1755
Journal website: academicinspired.com/jised
DOI: 10.55573/JISED.118873

Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) for each model. Hence, the overall performance of the ARIMA models was evaluated in terms of in-sample goodness-of-fit and parsimony using the AIC and the BIC and the forecast accuracy of the models based on RMSE, MAE and MAPE. The model demonstrating superior in-sample and out-of-sample performance was selected to forecast the future crude birth rate (CBR) in Malaysia.

Findings and Discussion

The main aim of this study is to apply the ARIMA model to forecast Malaysia's Crude Birth Rate (CBR). The analysis begins by examining the historical trend of CBR in Malaysia from 2000 to 2023 using the time plot shown in Figure 1. The data reveal that Malaysia's CBR declined from 22.8 births per 1,000 population in 2000 to 13.6 in 2023, indicating a clear long-term downward trend. This continuous decline reflects structural socio-economic changes, including rapid urbanization, increased participation of women in higher education and the workforce, rising living costs, and improved access to family planning services (Tey et al., 2012; Department of Statistics Malaysia, 2024). Although the overall pattern is downward trend, the Malaysia's CBR also shows a minor short-term fluctuation which shows a slight increase from 17.3 to 17.9 births per 1,000 population between 2011 and 2012 (Department of Statistics Malaysia, 2024). This temporary increase is due to short-term economic improvements or policy initiatives aimed at encouraging higher fertility. However, the declining pattern quickly returned, and a more significant decline was observed after 2019. This decline might result from the COVID-19 pandemic which led to economic instability and might have postponed family planning decisions (Ahmad, 2025).

The historical CBR dataset was then divided into in-sample and out-sample sets using a 70:30 split for model development. Specifically, 70% of the data were allocated for in-sample model estimation, while the remaining 30% were reserved for out-of-sample validation. Then the ARIMA models were estimated using the first 70% of the data from the years 2000 to 2016 and the last 30% from the years 2017 to 2023 to evaluate the forecast accuracy for each of the candidate models. In the initial stage of ARIMA model development, the stationarity of the original CBR series was tested. Based on Figure 1, the plot clearly shows that the series is not stationary since there is a trend component in the series. This pattern suggests that the mean is not stable over time, providing evidence that the CBR series is non-stationary. Then, the ADF statistics was used to confirm this stationarity condition, and the results are shown in Table 1.

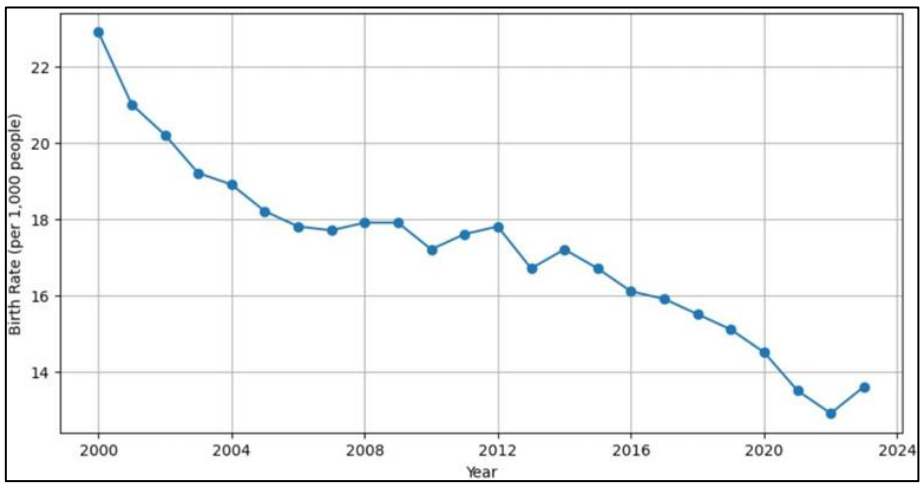


Figure 1: Trend of Birth Rate in Malaysia from year 2000 to 2023

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eISSN: 0128-1755
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DOI: 10.55573/JISED.118873

Table 1: Result of Augmented Dickey-Fuller (ADF) test

Series	ADF Statistic	*p*-value	Conclusion
Original CBR	-2.4630	0.1247	Series not stationary
First Difference CBR	-3.1174	0.0253	Series is stationary

The ADF test statistic for original CBR is -0.7396 with the *p*-value is 0.8362 (*p*-value is greater than the 5% level of significance). This result indicate that the original series is non-stationary since null hypothesis of the presence of a unit root cannot be rejected. Consequently, differencing is required to achieve stationarity before fitting an ARIMA model. This transformation is crucial because ARIMA models require a stationary series to generate valid and reliable forecasts. The ADF test of first difference CBR series in Table 1 shows that the series is stationary with the ADF statistic of –3.1174 and a *p*-value of 0.0253 which significant at 1% level of significance. This result confirms that the data are ready for model identification.

Next, model identification process was conducted using ACF and PACF plots of the first difference series. The plots in Figure 2 were examined to identify the potential orders of the AR and MA components of ARIMA model. The ACF plot exhibited a significant spike at lag 1, followed by a rapid decline in subsequent lags, suggesting the presence of a MA component of order $q = 1$ (MA (1)). Likewise, the PACF plot shows a sharp cutoff after lag 1 which indicate an AR component of order $p = 1$ (AR (1)). Therefore, the ACF and PACF patterns suggest that an ARIMA (1,1,1) model become the potential candidate for the series. Although the ACF and PACF analyses suggested ARIMA (1,1,1) as a potential model, several alternative specifications, namely ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (0,1,1), ARIMA (2,1,1), ARIMA (1,1,2), and ARIMA (2,1,2), were also estimated and evaluated. This approach is consistent with the Box–Jenkins methodology, which recommends examining multiple candidate ARIMA models and selecting the most appropriate specification based on model selection criteria and diagnostic checking (Box et al., 2015).

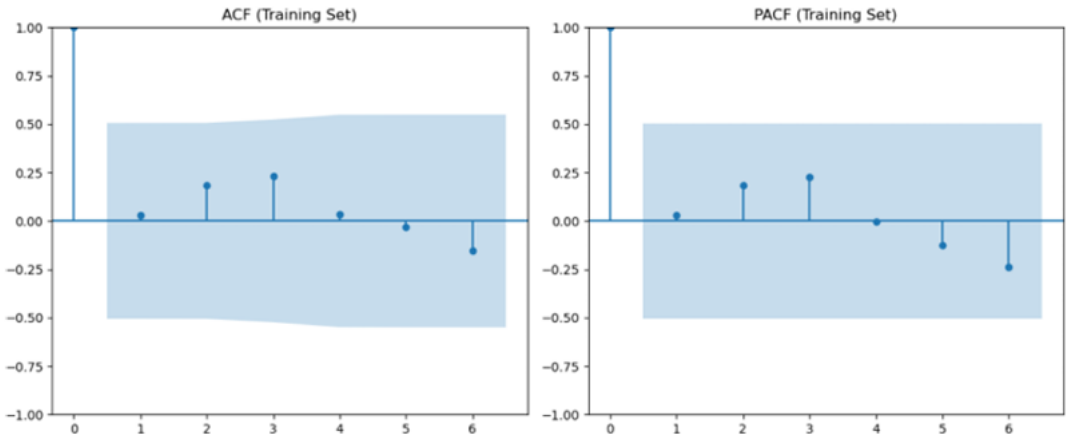


Figure 2: ACF and PACF Plot of First Difference Series of Crude Birth Rate in Malaysia

The adequacy of all candidate ARIMA models was first evaluated using the Ljung–Box test to determine whether the residuals are independently distributed and free from autocorrelation. As shown in Table 2, the *p*-values of the Ljung–Box test for all candidate models is greater than the 5% level of significance (*p*-value > 0.05). Therefore, the null hypothesis of no residual autocorrelation could not be rejected, indicating that the residuals of all fitted models behaved as white noise. This suggests that each candidate model adequately captures the temporal

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eISSN: 0128-1755
Journal website: academicinspired.com/jised
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dependence in the series and satisfies the residual diagnostic requirement for ARIMA modelling (Box et al., 2015; Hyndman & Athanasopoulos, 2021). After confirming the adequacy of the candidate models, the AIC and the BIC were used in selecting the best in-sample model. These information criteria evaluate model fit while penalizing model complexity, thereby reducing the risk of overfitting (Box et al., 2015). The ARIMA (1,1,2) model achieved the lowest AIC (31.51) and BIC (34.34) values compared to other the models which indicate the best balance between goodness-of-fit and model parsimony. Consequently, ARIMA (1,1,2) was become the best model in estimating CBR of Malaysia.

The forecast performance of the candidate ARIMA models was then further evaluated based on the out-of-sample validation using the RMSE, MAE and MAPE. As presented in Table 2, among all the candidate models, the ARIMA (1,1,2) model achieved the lowest RMSE (1.3445), MAE (1.1349), and MAPE (8.18%) which indicate the model produces the highest forecasting accuracy. Although the ARIMA (2,1,2) model produced comparable results, with an RMSE of 1.3461, an MAE of 1.1367, and an MAPE of 8.20%, its forecasting performance was slightly inferior to that of the ARIMA (1,1,2) model. Overall, the ARIMA (1,1,2) model was identified as the optimal model based on both the in-sample and out-of-sample evaluations, making it the most suitable model for forecasting the CBR series in this study.

Table 2: In-Sample and Out-of-Sample Performance of Candidate ARIMA Models

	In-sample evaluation			Out -sample evaluation		
Model	**Ljung-Box (p-value)**	**AIC**	**BIC**	**RMSE**	**MAE**	**MAPE**
ARIMA (1,1,0)	0.999997	36.62	38.04	2.1014	1.7911	12.90
ARIMA (2,1,0)	0.999993	35.61	37.74	2.1632	1.9147	13.70
ARIMA (0,1,1)	0.999998	37.27	38.69	2.2357	1.9328	13.89
ARIMA (1,1,1)	0.999996	35.75	37.87	1.5691	1.3414	9.65
ARIMA (2,1,1)	0.999995	36.35	39.18	1.7808	1.5617	11.19
ARIMA (1,1,2)	0.999992	31.51	34.34	1.3445	1.1349	8.18
ARIMA (2,1,2)	0.999992	33.49	37.04	1.3461	1.1367	8.20

Finally, the future CBR for the upcoming seven years of 2024 to 2030 was generated using ARIMA (1,1,2) model. As shown in Figure 3, the CBR in Malaysia is expected to continue its previous declining trend. According to the prediction, the number of births per 1,000 people would gradually decrease from 16.48 in 2024 to about 15.30 in 2030 as shown in Table 3. This reflects Malaysia's ongoing demographic transition toward lower fertility levels. The findings provide useful insights for national planning in areas such as the labour market, education, and healthcare systems. A sustained decline in birth rates is closely linked to population ageing and a shrinking workforce, which may lead to labour shortages, slower economic growth, and increasing pressure on public pension schemes and healthcare services.

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eISSN: 0128-1755
Journal website: academicinspired.com/jised
DOI: 10.55573/JISED.118873

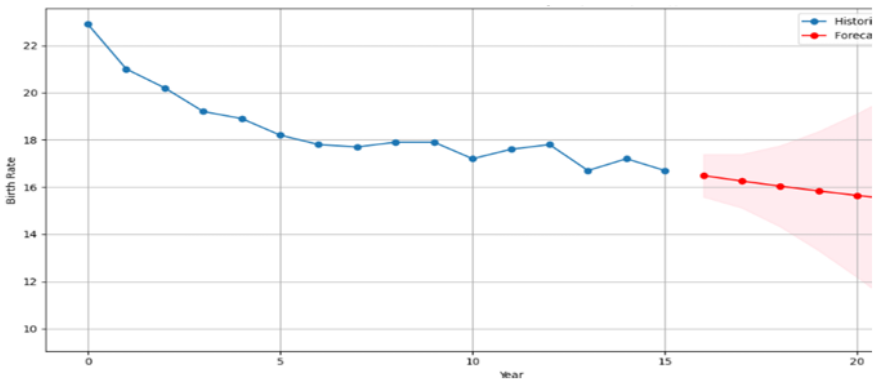


Figure 3: Trend of Actual and Forecast Birth Rate in Malaysia

Table 3: Forecast value for birth rate in Malaysia

Year	Birth Rates
2024	16.48
2025	16.25
2026	16.04
2027	15.58
2028	15.64
2029	15.47
2030	15.30

Conclusion

The historical trends of Malaysia's CBR (2000 to 2023) which obtained from DOSM was examined and it can be conclude that the CBR of Malaysia have a clear and persistent decline which decreased from 22.8 births per 1,000 population in 2000 to 13.6 in 2023. This downward trend is due to a broader socio-economic change, including rapid urbanization, delayed marriage, rising child-rearing costs, and greater participation of women in higher education and the workforce. Then, several ARIMA models were developed and evaluated. The ARIMA (1,1,2) model was identified as the most suitable in forecasting Malaysia' CBR where this model achieved the best balance between goodness of fit and superior out-of-sample forecasting performance. Forecasts CBR for the period 2024 to 2030 suggest that Malaysia's CBR will continue to decline, falling from 16.48 to 15.30 births per 1,000 population. If this trend continues, Malaysia is likely to face significant demographic challenges, including an ageing population, a shrinking workforce, and growing pressure on economic growth, as well as on pension systems and healthcare services. Overall, this study demonstrates that the ARIMA model provides a reliable and statistically robust approach for forecasting Malaysia's CBR. The findings offer valuable evidence to support proactive, data-driven demographic planning and policy development, contributing to long-term national resilience and sustainable development, particularly in relation to the United Nations Sustainable Development Goals (SDGs) 3 (Good Health and Well-being) and 8 (Decent Work and Economic Growth).

Suggestion for Future Research

Several recommendations can be made based on the findings of this study in order to improve the accuracy and reliability of future CBR in Malaysia. Although the standalone ARIMA model demonstrated strong forecast performance, it is limited in its ability to incorporate external factors that may influence CBR trends. Future research should therefore consider integrating relevant socio-economic and policy-related variables, such as child-rearing costs, parental leave policies, tax incentives, and changing societal norms, by employing more advanced models

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Volume: 11 Issues: 88 Special Issue [November, 2026] pp 1066-1078
Journal of Islamic, Social, Economics and Development (JISED)
eISSN: 0128-1755
Journal website: academicinspired.com/jised
DOI: 10.55573/JISED.118873

such as ARIMAX or machine learning techniques. Incorporating these exogenous variables would provide a more comprehensive understanding of the factors driving changes in the CBR. In addition, future studies should consider a longer historical series whenever available. Besides using yearly CBR, future researchers may consider conducting study using monthly or quarterly series that would enable researchers to capture short-term fluctuations and seasonal patterns which lead to more detailed and accurate forecasts. Future researchers could also explore hybrid forecasting approaches by combining ARIMA with advanced machine learning models, such as Artificial Neural Networks (ARIMA-ANN), Long Short-Term Memory (LSTM) networks, or the Prophet model that able to capture complex non-linear relationships, structural changes, and unexpected external events, such as global pandemics, which may significantly affect demographic patterns. Such approaches may further improve forecasting performance and provide more robust evidence to support demographic planning and policy formulation in Malaysia.

Acknowledgements
The authors would like to express their sincere gratitude to Universiti Teknologi MARA (UiTM) Cawangan Negeri Sembilan and UiTM Cawangan Pahang for providing the facilities and support necessary to conduct this study. The authors also thank the Department of Statistics Malaysia (DOSM) for providing the data used in this research.

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DOI: 10.55573/JISED.118873

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