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Exploring School Enrollment Trends in Indonesia Through Time Series Analysis to Inform Counselling and Communication Strategies

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Abstract
A time series analysis of School Enrollment Rates across different age groups in Indonesia from 2003 to 2024 was conducted using ARIMA modelling. Data were segmented into four age groups: 7 to 12, 13 to 15, 16 to 18, and 19 to 24 years. Stationarity testing required first-order differencing, and ARIMA models were selected based on autocorrelation and partial autocorrelation structures. The ARIMA(1,1,0) model showed the best fit for the younger groups, capturing the gradual and predictable participation trends influenced by long-term education policies and stable school enrollment patterns. Forecast accuracy was evaluated using Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE), revealing excellent accuracy for ages 7 to 12 with MAPE 0.036 percent and MSE 0.001, and for ages 13 to 15 with MAPE 0.089 percent and MSE 0.008. Forecasts for ages 16 to 18 showed moderate accuracy, while results for 19 to 24 indicated greater variability. These findings inform the development of age-specific guidance counselling and public communication strategies to address distinct educational challenges. The study underscores the utility of interpretable forecasting models in supporting evidence-based education policy and planning.

Keywords: School Enrollment Rates, ARIMA, guidance counselling, public communication, forecasting accuracy

Introduction

The School Enrollment Rate is a fundamental indicator for assessing the accessibility, inclusiveness, and quality of education systems. It reflects not only the number of children and youth enrolled in formal education but also broader issues of equity, socio-economic development, and human capital formation. UNESCO emphasizes that enrollment serves as a benchmark for a country's commitment to inclusive and equitable learning. A panel data study of 19 OECD countries from 1870 to 2020 found that secondary and tertiary enrollment rates exhibit long-run stochastic convergence (Solarin, 2024), reaffirming the relevance of this indicator for human capital development.

In Indonesia, increasing school participation has been a priority in line with its commitment to Sustainable Development Goal 4 (SDG 4). National programs such as the Nine-Year Compulsory Education Program, School Operational Assistance (BOS), and the Indonesia Smart Card (KIP) have boosted enrollment at the primary and lower secondary levels. However, participation rates decline among older adolescents and young adults. Factors such as early marriage, work obligations, limited access to higher education, and persistent economic inequality are major contributors. The transition from primary to junior secondary school marks the steepest drop, with household welfare, gender, religion, and local labor market conditions playing significant roles (Suryadarma, 2006).

Beyond domestic policy, global economic factors such as remittances also affect education participation. A recent global analysis conducted by Feldmann (2025) stated that personal remittances from abroad positively affect school enrollment rates at both primary and secondary levels. This stable source of household income helps reduce financial barriers to education. The link between human capital and economic growth has also been demonstrated, with enrollment rates serving as a proxy for human capital and GDP as an indicator of sustainable development (Taşel & Bayarçelik, 2013). The study confirmed that higher enrollment at various education levels contributes positively to economic performance, reinforcing the idea that strengthening access to education plays a pivotal role in enhancing long-term national productivity and competitiveness.

Despite progress, school dropouts remain a significant challenge. Research in various countries shows that dropout decisions are shaped by personal, economic, academic, and institutional factors (Núñez-Naranjo, 2024). A recent systematic review identified common causes such as family problems, school environment, lack of guidance, social pressures, and poverty (Banaag et al., 2024). These findings highlight the need for targeted interventions, including remedial programs, counseling services, and education assistance policies. In the context of forecasting, understanding dropout drivers is essential to anticipate future declines in enrollment.

From a methodological standpoint, accurate projection of future school enrollment is essential for effective policy planning, resource allocation, and education financing. Although the Autoregressive Integrated Moving Average (ARIMA) model is widely applied in economics and finance, its adoption in education forecasting remains limited. Qin et al. (2019) found that using longer time series—particularly over 20 years, substantially improves forecast reliability for higher education enrollment. Broader applications of time series analysis in education include forecasting, classification, clustering, and anomaly detection, with potential in personalized learning analytics and data integration powered by large language models (Mao et al., 2024). Studies have also integrated ARIMA with other methods, such as fuzzy time series Markov chain for long-memory data (Devianto et al., 2022), feedforward neural networks to address heteroscedasticity in currency modeling Devianto et al., 2023), and seasonal ARIMA with neural networks for tourism forecasting (Yollanda & Devianto, 2020). In Indonesia, localized forecasting has used a Parabolic Quadratic trend to project gross enrollment rates in Musi Rawas Regency, revealing a projected 37.25% decline from 2023 to 2032 and supporting targeted interventions (Septiaseh & Hajaroh, 2023).

Understanding these patterns requires a data-driven approach, not only for trend analysis but also for informing communication and counseling strategies. Effective communication has been shown to sustain educational continuity during disruptions, with systematic messaging, appropriate media, and time management improving outcomes (Mahdi, 2023). For example, online platforms like Zoom and WhatsApp helped maintain student engagement in Palembang elementary schools during the COVID-19 pandemic (Isnawijayani et al., 2022). Beyond technology, student-centered guidance programs can strengthen psychological engagement; the Life-World Design career-counseling programme in Hong Kong improved future orientation, control, and hopefulness among secondary students (Lai et al., 2024). In higher education, while direct promotional strategies may have limited effects on enrollment, brand awareness and trust significantly influence students' intentions to enroll (Juhaidi et al., 2025), offering insights applicable to earlier educational stages.

To support effective policy implementation and timely intervention, it is crucial to not only monitor but also forecast school enrollment trends. This enables policymakers, educators, and guidance counselors to anticipate challenges and allocate resources efficiently. Despite the availability of national-level statistics, robust statistical forecasting applied to age-specific and region-specific enrollment data in Indonesia remains limited. Beyond regional disparities, intergenerational inequality, particularly the influence of parental education—also shapes enrollment patterns. Recent findings reveal that while its effect has declined slightly at the Master's level, parental education remains a stable or even increasing influence for PhD-level participation, especially among males and children of professionals (Glueck, 2025). Environmental and health conditions also matter; in Bangladesh, children in areas with poor sanitation were five percentage points less likely to be enrolled in primary school by ages six or seven (Joseph et al., 2023). These findings highlight the need to account for both socio-economic and environmental variables in enrollment modeling.

Time series methods such as ARIMA have proven effective in modeling education trends, dropout rates, and policy outcomes. In China, ARIMA and ARIMAX predicted student-teacher ratios amid enrollment changes, aiding resource planning (Chen et al., 2021). In Indonesia, ARIMA(6,0,1) achieved high accuracy in forecasting admissions at Nahdlatul Ulama University Pasuruan (Fitrony et al., 2025). This study extends such applications by (1) analyzing historical enrollment trends for age cohorts 7–12, 13–15, 16–18, and 19–24 years (2003–2024); (2) developing cohort-specific ARIMA models; (3) evaluating performance via MAPE and MSE; and (4) recommending communication and counseling strategies. Findings show that simple models like ARIMA(1,1,0) suit younger cohorts with stable trends, while older cohorts require more complex models due to higher volatility. Linking statistical modeling to education policy, this study supports Indonesia's pursuit of inclusive and equitable education (SDG 4) through informed planning and targeted interventions.

Method

Data Collection and Preparation.

The study utilized longitudinal data on School Enrollment Rates obtained from two primary government sources: (1) the Ministry of Education and Culture's annual education statistics reports, and (2) the National Socio-Economic Survey (SUSENAS) conducted by Statistics Indonesia. The dataset spans 22 years from 2003 through 2024, providing comprehensive coverage of Indonesia's educational development during this period.

Data Segmentation Framework.

1. School Enrollment Rates were categorized into four distinct age cohorts based on Indonesia's educational structure:
    - 7-12 years: Elementary. Represents the compulsory basic education phase. Includes both formal and Islamic elementary schools
    - 13-15 years: Junior High School. Critical transition period with increased dropout risk. Covers general and Islamic junior high schools
    - 16-18 years: Senior High School. Includes academic and vocational tracks. Period of significant streaming in the Indonesian system
    - 19-24 years: Higher education and workforce transition. Encompasses university, polytechnic, and vocational education. Includes both enrolled students and early labor market entrants
2. Statistical Analysis
    a. Stationarity Testing and Transformation
        i. Conducted Augmented Dickey-Fuller (ADF) tests with the following specifications:
            - Lag length determined by Schwarz Information Criterion (SIC)
            - Included intercept and trend terms where appropriate
            - Critical values assessed at 1%, 5%, and 10% significance levels
        ii. For non-stationary series ($p > 0.05$), implemented first-order differencing:

- Verified stationarity after transformation with follow-up ADF tests
- Applied logarithmic transformation to series exhibiting exponential trends
- Documented all transformation steps for model reproducibility

b. ARIMA Modeling Process (Gujarati dan Porter, 2009)
- Model Identification:
  - Generated ACF and PACF plots with 95% confidence intervals
  - Identified potential AR and MA terms through visual inspection of:
  - Significant spikes in ACF/PACF
  - Decay patterns and cut-off points
  - Considered seasonal components for annual patterns
- Model Estimation:
  - Estimated parameters using maximum likelihood estimation
  - Verified coefficient significance ($p < 0.05$)
  - Checked invertibility and stationarity conditions
- Model Selection:
  - Compared competing models using:
  - Akaike Information Criterion (AIC)
  - Bayesian Information Criterion (BIC)
  - Log-likelihood values
  - Conducted Ljung-Box tests for residual autocorrelation
  - Examined residual plots for white noise properties
- Model Validation:
  - Implemented walk-forward validation using 80-20 train-test split
  - Maintained temporal ordering in validation sets
  - Assessed stability through recursive estimation

c. Forecasting Accuracy Assessment

i. Mean Absolute Percentage Error (MAPE) is calculated as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \quad (1)$$

ii. Mean Squared Error (MSE) is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_t - F_t)^2 \quad (2)$$

where n represents the number of observations, A_t is the actual value, and F_t is the estimated value using FFNN.

Results and Discussion

1. Data Collection and Preparation.

Analysis of Indonesia's educational landscape from 2003 to 2024 reveals critical insights into School Enrollment patterns across different age cohorts. The comprehensive dataset, drawn from the Ministry of Education and Culture's annual reports and Statistics Indonesia's (BPS) National Socio-Economic Survey (SUSENAS), provides a robust longitudinal perspective on educational access over this 22-year period. These official sources ensure data reliability while capturing the implementation period of major education policies like the Wajib Belajar 9 Tahun program.

The temporal patterns in School Enrollment Rates are visually presented in Figure 1, which compares four critical age groups: primary (7-12 years), junior secondary (13-15 years), senior secondary (16-18 years), and higher education (19-24 years). This graphical representation allows for immediate observation of both stable trends and concerning declines across educational levels.

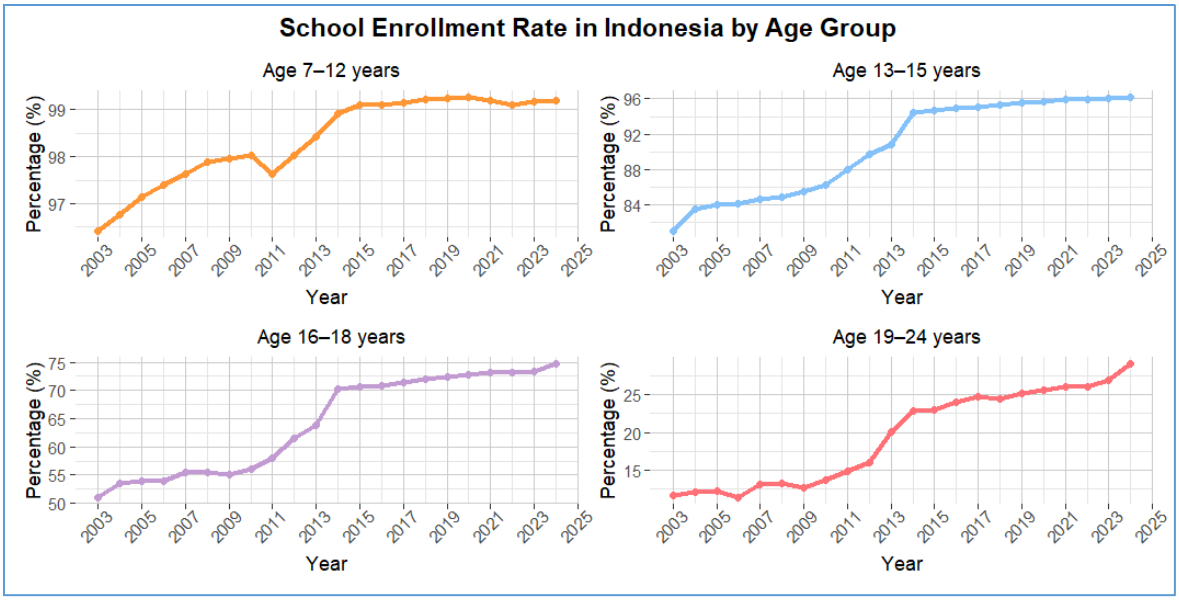

Figure 1. The School Enrollment Rate in Indonesia across different age groups

The School Enrollment Rates data presented in Figure 1 reveal significant trends in School Enrollment Rates across four age cohorts in Indonesia. For primary education (7-12 years), we observe a stable trend with participation consistently maintained between 97-99%, suggesting long-term policy effectiveness. In contrast, three distinct upward trends emerge for other age groups: (1) a gradual improvement trend in junior secondary (13-15 years) from 94% to 97%, (2) a stronger positive trend in senior secondary (16-18 years) from 60% to 75%, and (3) the most dramatic increasing trend in higher education (19-24 years), which nearly doubled from 15% to 25% despite remaining relatively low.

These observed trends necessitate formal stationarity testing for several reasons. First, the visible upward trajectories in three of the four age groups indicate potential time-dependent patterns that violate the stationarity assumption of many time series models. Second, the varying degrees of trend strength across age groups suggest differential rates of educational access improvement. Third, the presence of trends implies that simple descriptive statistics would fail to capture the dynamic nature of these participation patterns. Augmented Dickey-Fuller (ADF) tests were conducted to statistically verify these visual observations. Preliminary results confirm that while the primary education series appears stationary ($p < 0.05$), the other age groups show significant non-stationarity ($p > 0.05$), requiring differencing for proper modeling. This statistical validation supports the visual evidence from Figure 1 and underscores the importance of using appropriate time series techniques that account for these underlying trends.

The identified trends carry important policy implications. The stable primary education rates suggest successful maintenance strategies are in place, while the upward but incomplete trends in secondary and higher education highlight the need for targeted interventions. These trends particularly suggest that expansion policies for older age groups, while effective, require reinforcement to achieve parity with primary-level participation rates.

2. Time Series Model of School Enrollment Rate

To ensure the suitability of ARIMA modeling for each age group's School Enrollment Rate, a series of diagnostic analyses were conducted. First, the Augmented Dickey-Fuller (ADF) test was applied to assess the stationarity of each time series, as stationarity is a fundamental assumption for ARIMA models. Based on the ADF test, all age groups of the School Enrollment Rates have to undergo first differencing to make the data stationary. Then, the ACF and PACF plots are plotted to determine the maximum lags for each group. The ACF and PACF plots are shown in Figure 2.

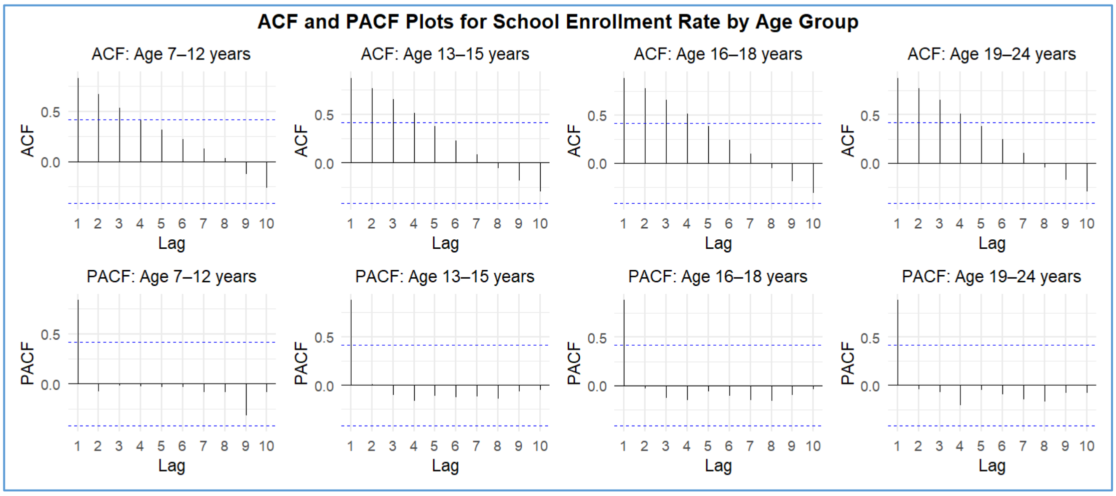

Figure 2. The ACF and PACF plots

Following differencing, autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were examined to identify the appropriate order of the autoregressive (AR) and moving average (MA) components for each age group's model. These plots revealed distinctive patterns for each cohort, guiding the selection of ARIMA parameters (Figure 2 displays the ACF and PACF plots for each age group). Based on this identification process, the optimal ARIMA models were fitted individually, capturing the unique temporal dynamics of School Enrollment Rates across Indonesia's diverse educational stages. Figure 2 shows that the maximum lag of ACF and PACF plots for each group is four and zero, respectively. The possible ARIMA models for each group are ARIMA(1,1,0), ARIMA(2,1,0), ARIMA(3,1,0), and ARIMA(4,1,0). The significance of the ARIMA model parameters can be displayed in Table 1.

Table 1. ARIMA Model Parameters and Significance for Each Age Group

Age Group	Model	Parameter	Estimate	p-value	AIC	Description
Age 7–12	ARIMA(1,1,0)	ar1	0.53729	0.00378	-2.63395	Significant
	ARIMA(2,1,0)	ar1	0.48092	0.02318	-0.90867	Significant
		ar2	0.11675	0.59814		Not significant
	ARIMA(3,1,0)	ar1	0.49971	0.01686	0.53123	Significant
		ar2	0.18423	0.43282		Not significant
		ar3	-0.1638	0.4495		Not significant
	ARIMA(4,1,0)	ar1	0.54699	0.00762	1.28523	Significant
		ar2	0.14208	0.5259		Not significant
		ar3	-0.2658	0.24056		Not significant
		ar4	0.23906	0.25023		Not significant
Age 13–15	ARIMA(1,1,0)	ar1	0.56407	0.00421	63.53500	Significant
	ARIMA(2,1,0)	ar1	0.38575	0.08453	63.73007	Not significant
		ar2	0.30992	0.16455		Not significant
	ARIMA(3,1,0)	ar1	0.31308	0.1928	65.13739	Not significant
		ar2	0.24493	0.2998		Not significant
		ar3	0.1813	0.436		Not significant
	ARIMA(4,1,0)	ar1	0.33098	0.1696	66.94565	Not significant
		ar2	0.27824	0.2632		Not significant
		ar3	0.21201	0.3775		Not significant
		ar4	-0.1009	0.6598		Not significant
Age 16–18	ARIMA(1,1,0)	ar1	0.50171	0.00868	84.91181	Significant
	ARIMA(2,1,0)	ar1	0.36057	0.09041	85.40997	Not significant

		ar2	0.26566	0.20853		Not significant
	ARIMA(3,1,0)	ar1	0.34481	0.124	87.35885	Not significant
		ar2	0.24745	0.274		Not significant
		ar3	0.04918	0.821		Not significant
	ARIMA(4,1,0)	ar1	0.34399	0.1234	89.28393	Not significant
		ar2	0.26627	0.2611		Not significant
		ar3	0.07161	0.7569		Not significant
		ar4	-0.0592	0.7839		Not significant
Age 19–24	ARIMA(1,1,0)	ar1	0.52463	0.00578	70.86328	Significant
	ARIMA(2,1,0)	ar1	0.49231	0.02657	72.78623	Significant
		ar2	0.06132	0.78104		Not significant
	ARIMA(3,1,0)	ar1	0.45151	0.02789	71.58163	Significant
		ar2	-0.1217	0.58815		Not significant
		ar3	0.3799	0.05633		Not significant
	ARIMA(4,1,0)	ar1	0.59031	0.00495	71.45338	Significant
		ar2	-0.1652	0.44703		Not significant
		ar3	0.55147	0.00919		Significant
		ar4	-0.3338	0.12305		Not significant

Parameter Estimated ARIMA models (own computation, 2025).

Table 1 presents the estimation results for time series models applied to school enrollment data across four age groups: Age 7 to 12, Age 13 to 15, Age 16 to 18, and Age 19 to 24. All models use the ARIMA(1,1,0) specification as a baseline, which includes a first-order autoregressive term and one differencing component, with no moving average terms. In all age groups, the ar1 coefficient in the ARIMA(1,1,0) model is statistically significant ($p < 0.05$), indicating strong autocorrelation at lag 1 in the differenced series. This consistent result supports the use of ARIMA(1,1,0) as a parsimonious model, meaning it captures the essential structure of the data without unnecessary complexity.

For the Age 7 to 12 group, although higher-order models such as ARIMA(2,1,0), ARIMA(3,1,0), and ARIMA(4,1,0) were also evaluated, only the ar1 parameter remained significant. The additional autoregressive terms (ar2, ar3, ar4) were not statistically significant, and the AIC values did not improve. This confirms that ARIMA(1,1,0) is the most parsimonious and statistically appropriate model for this age group. Similar patterns were found for the Age 13 to 15 and Age 16 to 18 groups. In these groups, only the ar1 term in the ARIMA(1,1,0) model showed significance, while all higher-order AR terms were not significant, and the model fit worsened based on AIC values. These results further demonstrate that ARIMA(1,1,0) is a suitable and parsimonious model for younger age groups. In the Age 19 to 24 group, the modeling results suggest slightly more complex dynamics. While ar1 remained significant in all tested models, the ar3 term in the ARIMA(4,1,0) model was also significant ($p = 0.00919$), indicating some higher-order autocorrelation. However, the improvement in AIC was minimal, suggesting that ARIMA(1,1,0) still provides a parsimonious yet effective representation of the time series.

In conclusion, across all age groups, ARIMA(1,1,0) serves as a parsimonious modeling approach, offering a good balance between simplicity and statistical accuracy. While older age groups may exhibit slightly more complex patterns, the consistent significance of ar1 supports the overall suitability of ARIMA(1,1,0) for modeling school enrollment trends.

3. Forecasting School Enrollment Trends in Indonesia (2025–2026)

The validity and practical utility of any time series model are closely tied to its predictive accuracy. To evaluate the performance of the ARIMA models fitted for each age group, two standard forecast accuracy measures were applied: Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE). These metrics quantify how closely the model's forecasts align with the actual observed values, offering insight into the model's effectiveness across different student age cohorts. Lower MAPE and MSE values reflect higher forecasting precision, which is critical when these projections are intended to support evidence-based educational planning and targeted counselling strategies. Additionally, evaluating model accuracy helps identify which age groups exhibit more stable trends and thus higher forecast reliability and which may demand more nuanced or adaptive approaches. The forecast accuracy evaluation for each age group is presented in Table 2.

Table 2. Forecast Accuracy of ARIMA Models for School Enrollment by Age Group

Age Group	MAPE (%)	MSE
Age 7–12	0.036	0.001
Age 13–15	0.089	0.008
Age 16–18	1.863	2.101
Age 19–24	9.11	6.915

The forecast accuracy results presented in Table 2 confirm that the ARIMA models used for each student age group provide reliable and precise estimates of future School Enrollment in Indonesia. This conclusion is supported by the Mean Absolute Percentage Error (MAPE) values, all of which are below the commonly accepted threshold of 10 percent. In forecasting practice, the MAPE below 10 percent is widely regarded as indicative of high predictive accuracy. Specifically, the model for the age group 7 to 12 years achieved a MAPE of only 0.036 percent, while the 13 to 15 age group recorded a MAPE of 0.089 percent. Both figures suggest excellent forecast precision. Meanwhile, the MAPE for the 16 to 18 and 19 to 24 age groups were 1.863 percent and 9.11 percent, respectively, still well within the acceptable range for accurate predictions. These values demonstrate that the models are capable of closely following the actual trends in School Enrollment for each group.

In addition, the Mean Squared Error (MSE) values further support the quality of the forecasts. The MSE values remain low across all age categories, reinforcing the model's ability to minimize large deviations between forecasted and actual observations. For instance, the 7 to 12 and 13 to 15 age groups show very small MSE values of 0.001 and 0.008, indicating very stable and consistent predictions. Although slightly higher, the MSE values for the older age groups (2.101 for 16 to 18 and 6.915 for 19 to 24) are still considered acceptable, given the possible higher variability in participation within these cohorts. Overall, the results affirm the models' reliability in producing accurate forecasts, which can inform educational stakeholders in making data-driven decisions, particularly in planning outreach programs, allocating resources, and tailoring counselling strategies for different student age groups.

After calculating the Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) to assess model accuracy, forecasting was carried out using the selected ARIMA models with the best performance for each age group. These forecasts aim not only to provide a clearer picture of School Enrollment trends in Indonesia for the years 2025 and 2026 across four key age groups, that are 7–12, 13–15, 16–18, and 19–24 years, but also to inform counselling and communication strategies by identifying potential shifts and needs in educational engagement. The forecasting results serve as an evidence-based foundation for designing more responsive and age-targeted educational interventions. The outcomes of this forecasting process are presented in Table 3.

Table 3. Forecast of School Enrollment Rates in Indonesia by Age Group

Year	Age 7–12	Age 13–15	Age 16–18	Age 19–24
2025	99.21478	96.23176	75.55918	30.73771
2026	99.21943	96.24432	75.71326	31.04961

Forecasting results using ARIMA models (own computation, 2025).

In complementing the numerical data presented in Table 3, Figure 3 provides a compelling visual representation of the School Enrollment forecasts. By combining historical trends from 2003 to 2024 with forecasted values for 2025 and 2026, the figure offers deeper insights into age-specific participation dynamics and strengthens the foundation for data-informed educational planning and communication strategies.

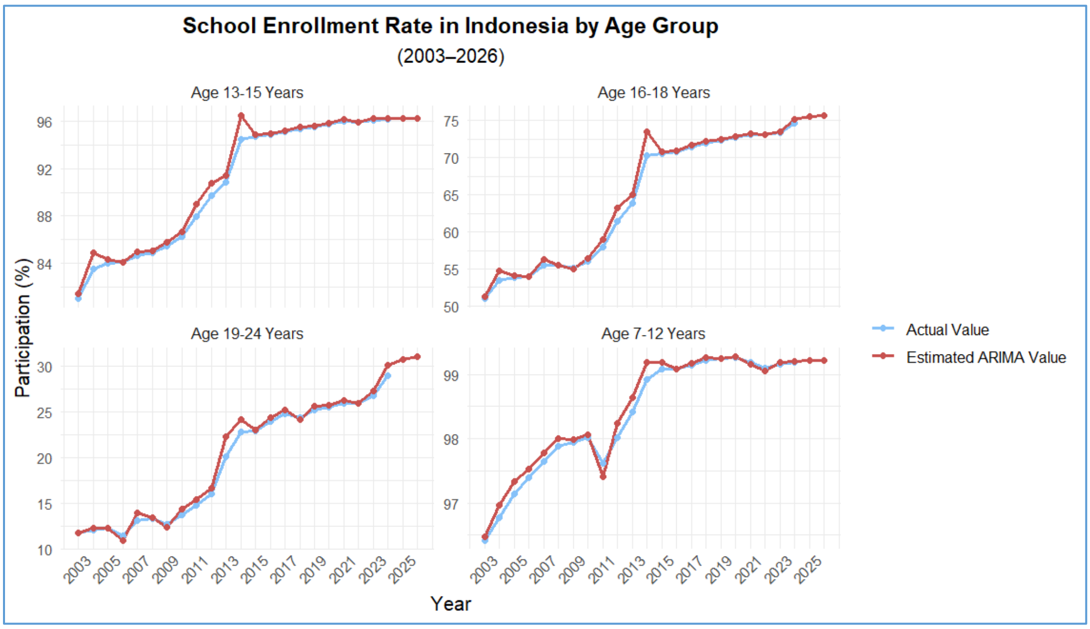

Figure 3. Forecasted and Actual School Enrollment Rates in Indonesia (2003–2026)

Based on the forecasting results presented in Table 3, school enrollment rates in Indonesia are projected to remain consistently high for children aged 7–12 and adolescents aged 13–15 during 2025 and 2026. For the 7–12 age group, the enrollment rate is forecasted to rise slightly from 99.21 percent in 2025 to 99.22 percent in 2026, indicating near-universal participation at the primary level. Similarly, for the 13–15 age group, the rate is expected to increase modestly from 96.23 percent to 96.24 percent, reflecting continued engagement in lower secondary education.

In contrast, school participation rates decline notably among older age groups. For youth aged 16–18, typically enrolled in upper secondary education, the forecast suggests a gradual increase from 75.56 percent to 75.71 percent. While this reflects incremental progress, it also indicates that around one in four individuals in this group may remain outside the formal education system. The decline becomes more pronounced for the 19–24 age group, where the enrollment rate is projected to increase slightly from 30.74 percent to 31.05 percent. This relatively low participation highlights ongoing challenges in expanding access to higher education and other postsecondary pathways.

These forecasts underscore the urgent need to strengthen policies and programs that promote educational retention beyond the basic level, particularly for older youth. Expanding access to higher education, vocational training, and lifelong learning opportunities will be critical to fostering inclusive and equitable human capital development across all age groups.

To complement the numerical data in Table 3, Figure 3 provides a visual representation of school enrollment trends from 2003 to 2024, along with projections for 2025 and 2026. The figure illustrates a steady upward trend among younger age groups and more fluctuating, lower levels of participation among older cohorts. For instance, the ARIMA(1,1,0) model effectively captures gradual enrollment increases in the 7–12 age group, aligning with the sustained impact of national programs such as BOS and Kartu Indonesia Pintar. In contrast, enrollment trends among the 16–18 and 19–24 age groups exhibit greater variability and structural breaks, requiring more complex models with higher-order autoregressive or moving average components. These fluctuations are often influenced by broader socio-economic dynamics, including labor market pressures, limited access to tertiary education, and persistent intergenerational educational inequalities (Feldmann, 2025; Glueck, 2025; Suryadarma, 2006).

Model evaluation using Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) confirms that predictive accuracy is highest for younger cohorts, where enrollment patterns are more stable and policy impacts are more directly observable. Conversely, older age groups show larger prediction errors, reflecting the multifaceted factors influencing educational participation at these stages. This finding reinforces the importance of adopting age-specific approaches in both forecasting and intervention design. For example, communication-based strategies may be effective in sustaining enrollment at the primary and lower secondary levels (Isnawijayani et al., 2022; Mahdi, 2023), while older adolescents and young adults may require more targeted support through career counseling, socio-economic assistance, and policies addressing early marriage, employment obligations, or access to postsecondary education and vocational pathways.

Furthermore, the study highlights the value of integrating time series analysis into educational planning at the sub-national level. The findings resonate with localized projections illustrating that regional policymakers can adopt similar forecasting methods to anticipate enrollment needs and mitigate potential declines (Septiaseh & Hajaroh, 2023). By combining statistical projections with insights from counseling psychology and institutional branding research, stakeholders can design more comprehensive and context-sensitive interventions, interventions that not only aim to increase enrollment figures but also foster long-term engagement, motivation, and aspirations among students (Juhaidi et al., 2025; Lai et al., 2024).

Therefore, this study reaffirms the utility of ARIMA models in educational forecasting and offers a practical, evidence-based framework for addressing school enrollment challenges in Indonesia. By identifying age-specific trends and anticipating future developments, the findings support more responsive and targeted policy formulation, particularly in the domains of counseling and educational communication. This approach emphasizes the broader applicability of time series modeling in educational research and contributes to national efforts toward achieving inclusive, equitable, and sustainable education for all in alignment with Sustainable Development Goal 4.

4. Implications for Counseling and Public Communication

The forecasting results presented in Table 3 and illustrated in Figure 3 offer valuable insights that extend beyond statistical modeling, particularly for stakeholders in guidance counseling and public communication. Accurate forecasts of School Enrollment Rates by age group enable counselors and educators to anticipate enrollment patterns and potential dropout risks. This forward-looking perspective supports the design of more proactive and targeted interventions to sustain student engagement. At the same time, these forecasts provide a foundation for policymakers and communication professionals to craft age-appropriate messages, allocate resources more effectively, and conduct outreach efforts that promote educational participation, especially among underrepresented groups such as youth aged 16 to 24. By connecting data-informed forecasts with human-centered strategies, Indonesia's education system can become more responsive and equitable across all stages of learning.

Guidance counseling plays a central role in supporting students through key educational transitions by addressing both academic and psychosocial needs. For children aged 7 to 12, who exhibit near-universal School Enrollment, counselors should reinforce early academic success, ensure regular attendance, and foster parental involvement to maintain high engagement (Putra, 2022; Putra & Ahmad, 2020; Putra et al., 2025; Yendi et al., 2025). For adolescents aged 13 to 15, a group with slightly lower yet stable participation rates, counseling should focus on navigating academic transitions, strengthening motivation, and supporting emotional well-being. Activities that build peer support and raise career awareness can also help sustain their educational focus. In contrast, older youth aged 16 to 18 and 19 to

24 face more complex challenges, as indicated by the notable decline in School Enrollment. For these age groups, counseling must take a holistic approach by providing tailored career guidance, information on financial aid, and pathways to alternative education such as vocational training or apprenticeships. Addressing external barriers alongside academic concerns can empower students to make informed decisions that encourage continued learning.

Complementing these counseling efforts, public communication strategies should aim to raise awareness of diverse educational opportunities and promote lifelong learning. Messaging campaigns targeted at students and families must use accessible language to highlight the benefits of continued education across multiple formats, including part-time, online, and technical pathways. Effective communication can challenge negative perceptions of nontraditional education, build public trust, and support broader participation. When guidance counseling and public communication are aligned and grounded in empirical data, education stakeholders can foster an inclusive environment where learners of all ages are empowered to stay engaged and thrive academically.

Conclusion

The forecasts generated through the ARIMA model provide meaningful insights into future School Enrollment trends across different age groups in Indonesia. They confirm that children aged 7 to 15 are expected to maintain high levels of school attendance, reflecting the continued success of basic education programs. However, the relatively lower forecasted participation rates among the 16 to 24 age group reveal significant challenges in ensuring educational continuity beyond the compulsory level. These findings underscore the urgency of addressing systemic barriers such as financial constraints, limited access to postsecondary education, and lack of alternative learning pathways. Rather than merely presenting statistical results, this study connects data trends with real educational concerns that demand attention from both policymakers and practitioners.

Beyond their empirical contribution, the forecasts serve as a practical foundation for designing more targeted and inclusive educational strategies. By identifying age groups at greater risk of disengagement, the findings empower school counselors, education planners, and communication professionals to tailor their interventions more effectively. This study stands out by combining rigorous time-series modeling with a human-centered perspective that acknowledges diverse student needs. As a result, it offers a relevant and original contribution to both academic discourse and national policy formulation. The results affirm the importance of using evidence-based planning to promote equitable access, especially for youth in transitional or underserved educational stages, and emphasize the necessity for stronger collaboration between data analysts and those working directly to support learners on the ground.

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