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Designing a Revenue Blueprint for JKN: A Hybrid Time-Series and AI Forecasting Approach

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Abstract

Reliable contribution-revenue forecasting is important for the financial planning of Indonesia's National Health Insurance (JKN) program. This study develops and evaluates a hybrid ARIMA-LSTM framework using a reconstructed national monthly revenue series for January 2021-December 2024. Model development used 36 monthly observations from 2021-2023, while January-December 2024 was reserved for rolling-origin one-step-ahead evaluation. Actual inflation, payment-compliance, and unemployment indicators were incorporated as exogenous information, and a supplementary regional resilience analysis used provincial minimum wage, gross regional domestic product, and fiscal-capacity indicators. The hybrid model achieved a WAPE of 7.71% and a MAPE of 7.67%, compared with WAPE values of 8.18% for ARIMA and 9.98% for LSTM. ARIMA produced a slightly lower RMSE (1.65 trillion rupiah) than the hybrid model (1.72 trillion rupiah), indicating that the hybrid advantage was modest rather than universal. Revenue was positively associated with payment compliance ($r = 0.397$, $p = 0.005$) and negatively associated with the mean provincial open-unemployment rate ($r = -0.505$, $p < 0.001$), whereas contemporaneous inflation showed no meaningful linear association. The findings support the use of hybrid forecasting as one input to liquidity planning while emphasizing model uncertainty and transparent regional risk profiling.

Keywords: JKN contribution revenue, Hybrid ARIMA-LSTM, Rolling-origin forecasting, Regional economic resilience, BPJS Kesehatan.

1. Introduction

Indonesia's National Health Insurance program (Jaminan Kesehatan Nasional, JKN), administered by BPJS Kesehatan, requires a stable contribution-revenue stream to support continuous health financing. Revenue sustainability is influenced by participant payment behavior and broader economic conditions. Evidence from independent JKN participants shows that payment compliance is associated with socioeconomic capacity and payment-related factors (Wulandari et al., 2020), while national labor-market and economic statistics indicate persistent variation in employment and household purchasing conditions (Badan Pusat Statistik Indonesia, 2023, 2024). These conditions make reliable contribution-revenue forecasting relevant for short-term liquidity planning and longer-term financial management.

Regional heterogeneity adds an additional layer of uncertainty. Wage levels, regional economic output, labor-market conditions, and fiscal capacity differ substantially across Indonesian provinces. JKN participation and contribution patterns also vary across participant segments and regions (DJSN, 2024a, 2024b). Consequently, national revenue forecasting and regional economic-risk profiling should be treated as related but distinct analytical tasks: the former requires a coherent national time series, whereas the latter requires cross-sectional regional indicators.

Classical time-series models such as ARIMA are useful for representing linear temporal dependence, but may be insufficient when residual dynamics are nonlinear. LSTM networks can represent nonlinear sequential relationships, but their flexibility also increases the risk of overfitting when the sample is limited. Hybrid ARIMA-neural-network approaches have therefore been proposed to combine linear and nonlinear components, with empirical gains reported in several financial and economic forecasting applications (Dave et al., 2021; Fawzy et al., 2022; Hadwan et al., 2022; Alsuwaylimi, 2023; Sembiring et al., 2025). Their added value, however, must be demonstrated through genuine out-of-sample comparison rather than assumed a priori.

Accordingly, this study addresses the following question: does a hybrid ARIMA-LSTM residual-correction framework improve out-of-sample forecasts of monthly JKN contribution revenue relative to individual and benchmark models? The objectives are to (1) construct an auditable monthly national revenue series, (2) characterize its association with selected macroeconomic and operational indicators, (3) compare seasonal naive, ARIMA, SARIMA, ETS, LSTM, and hybrid ARIMA-LSTM forecasts under rolling-origin evaluation, and (4) develop a transparent regional economic-resilience segmentation using UMP, PDRB, and fiscal-capacity indicators.

2. Literature Study

2.1. ARIMA (Autoregressive Integrated Moving Average)

ARIMA models represent a time series through autoregressive, differencing, and moving-average components. Their main strengths are parsimonious parameterization, interpretable temporal structure, and well-established diagnostic procedures. Candidate orders can be evaluated using information criteria and residual diagnostics, while stationarity assessment helps determine whether differencing is required. ARIMA is especially useful as a linear benchmark against which more flexible models can be assessed (Alsuwaylimi, 2023).

A limitation of ARIMA is that nonlinear residual structure may remain after the linear component has been fitted. In economic forecasting, this limitation has motivated hybridization with neural-network models (Dave et al., 2021; Fawzy et al., 2022). In the present study, ARIMA is therefore used both as an individual forecasting model and as the linear component of the proposed hybrid framework.

2.2. LSTM (Long Short-Term Memory)

LSTM is a recurrent neural-network architecture designed to retain relevant information over sequential observations through forget, input, and output gates. This architecture can model nonlinear temporal relationships that are difficult to represent using purely linear methods. Applications in exchange-rate and financial forecasting demonstrate the flexibility of LSTM for volatile time series (Qureshi et al., 2023, 2024; Kalange, 2025).

Nevertheless, LSTM performance depends strongly on sample size, sequence length, architecture, regularization, and validation design. Sembiring et al. (2025) emphasize the importance of data partitioning when hybrid ARIMA-LSTM models are used for volatile series. Because the national monthly JKN sample is relatively short, the present study uses a deliberately small LSTM architecture, chronological validation, early stopping, and a fixed random seed to reduce overfitting risk.

2.3. Hybrid Model ARIMA-LSTM

The hybrid ARIMA-LSTM approach decomposes the forecasting task into two components. ARIMA first models the linear temporal structure. Its residuals, which contain the variation not represented by the linear component, are then modeled by LSTM. The final forecast is obtained by adding the ARIMA baseline and the LSTM residual correction. Similar residual-correction strategies have improved accuracy in some applications, although the size and consistency of the improvement vary across datasets (Dave et al., 2021; Hadwan et al., 2022; Fawzy et al., 2022; Sembiring et al., 2025).

2.4. JKN Contribution Revenue

JKN contribution revenue depends not only on participant numbers but also on payment regularity, labor-market conditions, and the economic capacity of participants. Wulandari et al. (2020) document factors associated with the compliance of independent JKN participants, while machine-learning approaches have increasingly been considered for insurance-premium prediction and personalization (Srinivasagopalan, 2023). Related Indonesian actuarial research has also treated payment lapse as a distinct risk component and demonstrated the sensitivity of premium calculations to financial assumptions, illustrating the broader importance of payment continuity in actuarial financial modeling (Zulkatri, Ringo, et al., 2026). These findings motivate the inclusion of observed compliance and labor-market indicators as supplementary information, while avoiding causal interpretation of simple correlations.

3. Methods

3.1Research Framework

This study uses a quantitative forecasting framework with a sequential residual-correction architecture. The primary unit of analysis is national monthly JKN contribution revenue. ARIMA models the linear component, and LSTM models either the revenue sequence directly or the residual sequence from ARIMA together with observed exogenous indicators. A separate cross-sectional module profiles provincial economic resilience. This separation avoids mixing repeated regional records with the national monthly forecasting series.

3.2 Data Collection and Variables

The analytical forecasting sample contains 48 monthly observations from January 2021 to December 2024. The first 36 months (2021-2023) were used for model development and the 12 months of 2024 were reserved for out-of-sample rolling-origin evaluation. The national target is monthly JKN contribution revenue in trillion rupiah. Exogenous information comprises monthly inflation, monthly payment compliance, and the annual mean of provincial open-unemployment rates (TPT), repeated within each corresponding year. Regional resilience uses the latest available provincial UMP, PDRB, and fiscal-capacity indicators as a supplementary cross-sectional profile.

Table 1. Variables, analytical level, frequency, and data sources

Variable	Level / frequency	Role	Source
JKN revenue	National / monthly, 2021-2024	Forecast target	BPJS Kesehatan / DJSN
Inflation	National / monthly	Exogenous	BPS
Payment compliance	National / monthly	Exogenous	BPJS Kesehatan / DJSN
TPT	Province / annual; mean used nationally	Exogenous	BPS
UMP	Province / latest available	Regional profile	Ministry of Manpower
PDRB per capita	Province / latest available	Regional profile	BPS
Fiscal capacity	Province / latest available	Regional profile	Ministry of Finance

Monthly JKN contribution revenue was compiled from DJSN contribution-revenue records and cross-checked against the audited BPJS Kesehatan program report (BPJS Kesehatan, 2023; DJSN, 2024b). Monthly payment-compliance data were obtained from DJSN monitoring records (DJSN, 2024c). Inflation and open-unemployment-rate data were obtained from Statistics Indonesia (Badan Pusat Statistik Indonesia, 2025a, 2025b). Provincial UMP, PDRB per capita, and fiscal-capacity indicators were obtained from the Ministry of Manpower, Statistics Indonesia, and the Ministry of Finance, respectively (Kementerian Ketenagakerjaan Republik Indonesia, 2025; Badan Pusat Statistik Indonesia, 2025c; Kementerian Keuangan Republik Indonesia, 2025). Some administrative monitoring records are not publicly accessible. The analytical dataset, preprocessing assumptions, and model code are documented and can be provided by the corresponding author subject to applicable data-sharing restrictions.

JKN contribution and compliance records were obtained from administrative and monitoring datasets compiled by BPJS Kesehatan and DJSN, while macroeconomic and regional indicators were obtained from BPS and Ministry of Finance sources. Some administrative source files are not publicly accessible. For reproducibility, the cleaned analytical series, preprocessing assumptions, and model code used in this revision are documented and can be provided by the corresponding author subject to applicable data-sharing restrictions.

3.3 Data Pre-processing

The original revenue workbook contained repeated records and cumulative/YTD values that could not be treated as consecutive monthly observations. The revised workflow therefore reconstructs one national observation per calendar month before any lag, rolling, or forecasting operation is performed. Monthly revenue is obtained from differences in cumulative contribution revenue. A small number of obvious non-monotonic transcription inconsistencies in the cumulative source series were corrected only when adjacent cumulative values and annual totals made the intended value unambiguous. In years for which the source provided a reliable February YTD total but not a reliable separate January value, the combined January-February amount was allocated equally across the two months solely to construct a regular monthly series. For 2024, the published January-February combined value of 25.70 trillion rupiah was therefore represented as 12.85 trillion rupiah in each month. These allocations are treated as preprocessing assumptions and are acknowledged as a study limitation. No centered moving averages or future observations were used to construct predictors. For LSTM estimation, scaling parameters were calculated from the available training history only and then applied to the next forecast origin, thereby preventing look-ahead leakage. All forecasting splits were chronological.

3.4 Hybrid Model Architecture

The proposed hybrid model uses ARIMA for the linear component and an LSTM network for the nonlinear residual correction.

3.4.1. Linear Modeling (ARIMA):

The general ARIMA model is expressed with the backshift operator B as:

$$\phi(B)\nabla^d Y_t = \theta(B)\varepsilon_t \tag{1}$$

where Y denotes observed monthly revenue at time t, d is the differencing order, $phi(B)$ is the autoregressive polynomial, $theta(B)$ is the moving-average polynomial, and epsilon denotes a white-noise innovation. Stationarity of the 2021-2023 training series was assessed using the Augmented Dickey-Fuller (ADF) test. Candidate ARIMA orders with p and q from 0 to 3 and d in {0,1} were compared by AIC and BIC. The selected model was ARIMA(0,1,1). Residual autocorrelation was evaluated with the Ljung-Box test.

3.4.2. Residual Calculation

The residual passed to the nonlinear correction model is defined as:

$$e_t = Y_t - \hat{L}_t \tag{2}$$

where e denotes the component not explained by the ARIMA baseline, Y is realized revenue, and the hatted L term is the ARIMA fitted or forecast value at time t.

3.4.3. Non-Linear Modeling (LSTM)

A Deep Learning LSTM is trained to predict these residuals (e_t). The LSTM input includes the regional economic indicators (UMP, GRDP, Fiscal Capacity) and macro indicators (Inflation, TPT). The output is Non-Linear Correction (N_t).The LSTM unit processes the input vector X_t (containing residuals and exogenous variables) through a series of gates:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f) \quad (3a)$$
$$i_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_i) \quad (3b)$$
$$\underline{C_t} = tanh(W_C \cdot [h_{t-1}, X_t] + b_C) \quad (3c)$$
$$C_t = f_t * C_{t-1} + i_t * \underline{C_t} \quad (3d)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) \quad (3e)$$
$$h_t = o_t \star tanh(C_t) \quad (3f)$$

Finally, the predicted non-linear component is derived from the hidden state:

$$\widehat{N}_t = W_y \cdot h_t + b_y \quad (4)$$

Which is:
i. $\widehat{N}_t$ (Non-Linear Forecast): The output of the LSTM model, representing the predicted residual correction.
ii. X_t (Input Vector): A multivariate vector containing the lagged residuals (e_{t-k}) and exogenous economic indicators (Inflation, Unemployment Rate, Normalized UMP, Normalized GRDP).
iii. f_t (Forget Gate): Determines what information from the previous cell state should be discarded (0 = forget, 1 = keep).
iv. i_t (Input Gate): Decides which new information from the current input will be stored in the cell state.
v. C_t (Cell State): The long-term memory of the network. It carries relevant information (like long-term economic trends) throughout the sequence chain.
vi. o_t (Output Gate): Controls what information from the cell state is output to the hidden state.
vii. h_t (Hidden State): The short-term memory or output of the LSTM cell at time t, used for the final prediction.
viii. σ (Sigmoid Function): Activation function that maps values between 0 and 1.
ix. $tanh$ (Hyperbolic Tangent): Activation function that maps values between -1 and 1
x. W and b: The weight matrices and bias vectors learned during the training process (e.g., W_f is the weight for the forget gate).
xi. $\underline{C_t}$: It represents the potential new information extracted from the current input X_t and the previous hidden state (h_{t-1}) that could be stored in the long-term memory.
xii. W_y (Weight Matrix): A learnable matrix that transforms the internal Hidden State h_t into the final output value.It acts as a linear regressor. It takes the complex features learned by the LSTM (stored in h_t) and maps them to the target scale (the magnitude of the revenue residual).
xiii. b_y (Bias Vector): A constant value added to the product of inputs and weights. It allows the activation function to be shifted to the left or right, ensuring the model can fit the data even when the input is zero.

3.4.4. LSTM Training and Hyperparameter Tuning

Hyperparameters were selected using chronological development data before the 2024 test period. The final direct LSTM used a 9-month look-back and 8 hidden units; the residual LSTM used the same 9-month look-back and 12 hidden units. Both used the Adam optimizer with a learning rate of 0.01, weight decay of 1e-4, mean squared error loss, a maximum of 160 epochs, and early stopping with a patience of 25 epochs. Within each refit, the last 20% of available training sequences was used for early stopping. A fixed random seed of 42 was used for reproducibility.

3.4.5. Hybrid Ensembling

The final hybrid forecast is the sum of the ARIMA baseline and the LSTM residual correction:

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t \tag{5}$$

This sequential construction makes the contribution of each model component explicit and permits direct comparison with the individual ARIMA and LSTM models.

3.4.6. Regional Economic Resilience Clustering

Regional profiling is treated separately from the national forecast. UMP and PDRB are log-transformed to reduce scale skewness, and all three regional indicators (log UMP, log PDRB, and fiscal capacity) are standardized across provinces:

$$z_{ij} = \frac{x_{ij} - \mu_j}{s_j} \tag{6}$$

where x is the value for a given province-indicator pair, mu is the cross-provincial mean for that indicator, and s is the corresponding standard deviation. Provinces are then grouped using K-means with $k = 3$, chosen a priori to provide an operational High-, Medium-, and Low-Risk classification without arbitrary 0.33/0.66 score thresholds or ad hoc indicator weights. The clustering objective is:

$$\min_{C_1, C_2, C_3} \sum_{k=1}^{3} \sum_{i \in C_k} \| z_i - \mu_k \|_2^2 \tag{7}$$

Cluster labels are assigned according to the mean standardized economic-capacity profile of each centroid. The segmentation should therefore be interpreted as an economic-resilience profile, not as a causal estimate of contribution default or revenue loss.

3.4.7. Rolling-Origin Model Evaluation

Forecast accuracy is evaluated using rolling-origin one-step-ahead forecasts for each month of 2024. At each origin, only information available up to the preceding month is used. This sequential evaluation is consistent with the prequential perspective used in actuarial prediction, in which one-step-ahead forecasts are evaluated using only information available before the subsequent observation is realized (Zulkatri, Azka, & Zainuddin, 2026). The benchmark set comprises seasonal naive, ARIMA, SARIMA, exponential smoothing (ETS), LSTM, and hybrid ARIMA-LSTM models. The following metrics are reported:

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} \left| Y_t - \hat{Y}_t \right| \tag{8}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(Y_t - \hat{Y}_t \right)^2} \tag{8}$$

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \tag{8}$$

$$\text{WAPE} = 100 \times \frac{\sum_{t=1}^{n} |Y_t - \hat{Y}_t|}{\sum_{t=1}^{n} |Y_t|} \tag{8}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2}{\sum_{t=1}^{n} (Y_t - \bar{Y})^2} \tag{8}$$

MAE and RMSE are expressed in trillion rupiah. MAPE and WAPE are reported in percent. R-squared is included because it was requested as an additional comparative statistic, but is interpreted cautiously for a short, low-variance test window.

4 Result and Discussion

4.1. Statistical Characteristics and Variable Correlation

Pearson correlation was used as a descriptive screening tool rather than as evidence of causality. Figure 1 summarizes contemporaneous relationships among monthly revenue, inflation, payment compliance, and the annual mean provincial TPT. The corresponding coefficients and significance tests are reported in Table 2.

Figure 1. Pearson correlation matrix of monthly JKN contribution revenue and national indicators.
Source: Authors' analysis.

Table 2. Pearson correlations between monthly JKN contribution revenue and selected indicators

Indicator	Pearson r	p-value	Interpretation
Inflation (t)	0.002	0.987	Negligible
Payment compliance (t)	0.397	0.005	Moderate positive
Mean provincial TPT (t)	-0.505	<0.001	Moderate negative
Inflation (t-1)	0.038	0.799	Negligible lagged
Payment compliance (t-1)	0.321	0.028	Positive lagged
Mean provincial TPT (t-1)	-0.530	<0.001	Negative lagged

Payment compliance shows a moderate positive contemporaneous association with revenue ($r = 0.397, p = 0.005$) and remains positively associated at a one-month lag ($r = 0.321, p = 0.028$). The mean provincial TPT is negatively associated with revenue both contemporaneously ($r = -0.505, p < 0.001$) and at a one-period lag ($r = -0.530, p < 0.001$). In contrast, inflation is essentially uncorrelated with revenue in this sample. These results do not establish causal effects; rather, they indicate which observed indicators contain descriptive information that may be useful in a forecasting context.

4.2. Temporal Dynamics of JKN Revenue

Figure 2 presents the reconstructed national monthly revenue series, with one national observation for each calendar month. The series is relatively stable through 2021-2023, mostly within a range of approximately 11-14 trillion rupiah per month, followed by somewhat greater month-to-month dispersion during 2024.

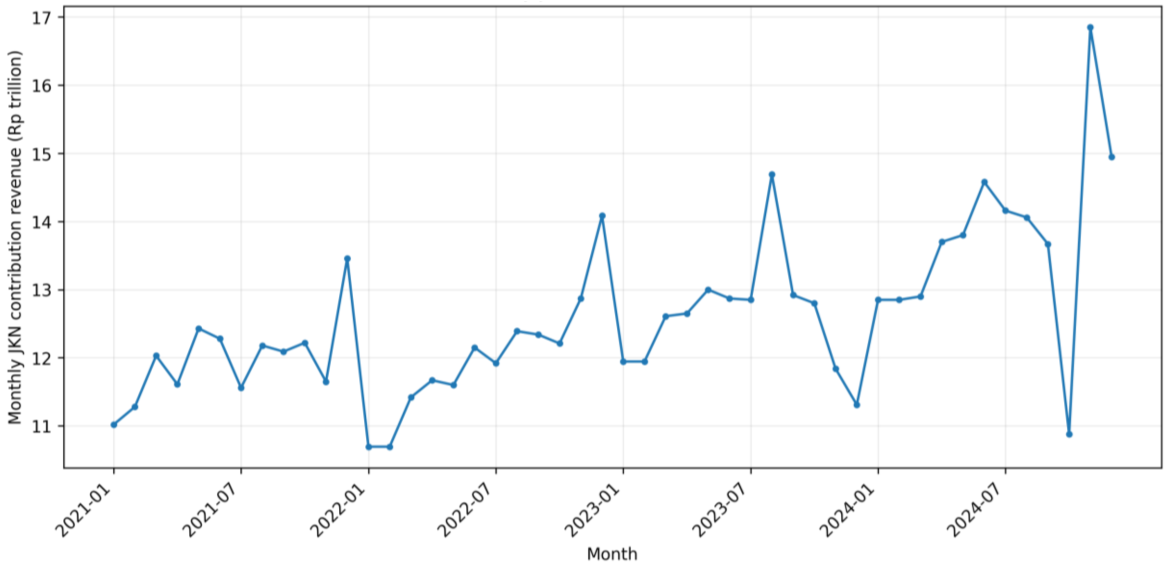

Figure 2. Historical Monthly JKN Contribution Revenue, 2021-2024.
Source: Authors' analysis.

The monthly JKN contribution revenue series shows relatively stable movements during 2021-2023, followed by greater month-to-month variation in 2024. The most notable fluctuations occurred toward the end of 2024, particularly the lower revenue realization in October and the subsequent increase in November. These variations provide an important basis for evaluating the ability of the forecasting models to capture short-term changes in contribution revenue.

4.3. Model Diagnostics and Comparative Forecast Performance

The ADF test on the 2021-2023 model-development series produced a statistic of -3.948 ($p = 0.0017$), rejecting the unit-root null at conventional levels. Candidate ARIMA specifications with d in {0,1} were nevertheless compared by information criteria; ARIMA(0,1,1) had the lowest AIC in the evaluated grid (AIC = 88.64; BIC = 91.76). Ljung-Box p-values of 0.966 at lag 6 and 0.975 at lag 12 indicated no material residual autocorrelation in the fitted linear component.

Table 3. Out-Of-Sample Rolling-Origin Forecast Performance, January-December 2024

Model	MAE / RMSE	MAPE / WAPE (%)	R^2
Seasonal naive	1.578 / 2.064	11.05 / 11.46	-1.263
ARIMA	1.127 / 1.651	8.15 / 8.18	-0.447
SARIMA	1.363 / 1.938	10.01 / 9.90	-0.995
ETS	1.456 / 2.039	10.72 / 10.57	-1.208
LSTM	1.374 / 1.739	9.68 / 9.98	-0.606
Hybrid ARIMA-LSTM	1.062 / 1.717	7.67 / 7.71	-0.566

Source: Authors' analysis.

The hybrid ARIMA-LSTM model achieved the lowest MAE (1.062 trillion rupiah), MAPE (7.67%), and WAPE (7.71%). Relative to ARIMA, the WAPE improvement was modest, decreasing from 8.18% to 7.71%. ARIMA retained the lowest RMSE (1.651 trillion rupiah compared with 1.717 trillion rupiah for the hybrid), demonstrating that the hybrid model is not uniformly superior across all error criteria. The negative R^2 values for all models reflect the limited variance and small size of the 12-month test window and indicate that substantial unexplained month-to-month variation remains. For this reason, WAPE, MAE, and RMSE receive greater emphasis than R^2 in the operational interpretation.

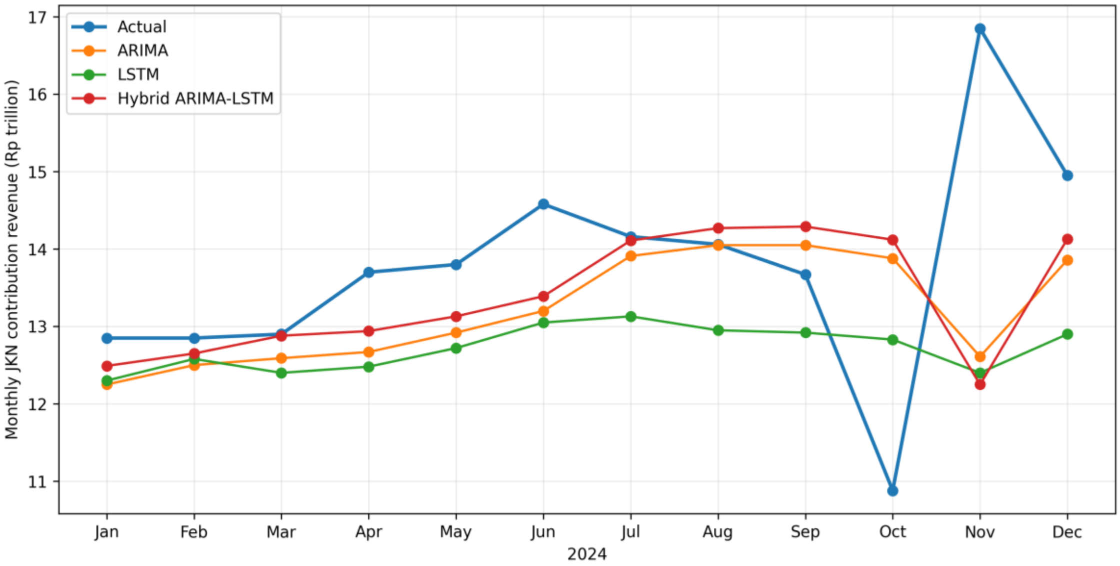

Figure 3. Rolling-origin one-step forecasts versus actual JKN contribution revenue in 2024.
Source: Authors' analysis

Figure 3 shows that ARIMA and the hybrid model follow the central revenue level reasonably closely for much of the year, while all models have difficulty with the sharp October-November swing. The hybrid residual correction improves average absolute and percentage error, but does not eliminate shock-related uncertainty. This supports a cautious interpretation: the hybrid architecture offers incremental forecasting value rather than evidence of complete robustness to structural disturbances.

4.4. Regional Economic Resilience Segmentation

The regional analysis uses a separate cross-sectional dataset so that provincial heterogeneity is not conflated with the national time series. Figure 4 displays the three K-means clusters in a two-dimensional principal-component projection. Provinces classified in the High-Risk economic-resilience cluster include, among others, Nusa Tenggara Timur, Nusa Tenggara Barat, DI Yogyakarta, Maluku, Jawa Tengah, Bengkulu, Sulawesi Barat, Papua Pegunungan, Gorontalo, Sumatera Barat, Sulawesi Tenggara, Lampung, Kalimantan Barat, and Aceh. These classifications reflect the joint standardized profile of UMP, PDRB, and fiscal capacity rather than fixed weights or manually selected thresholds.

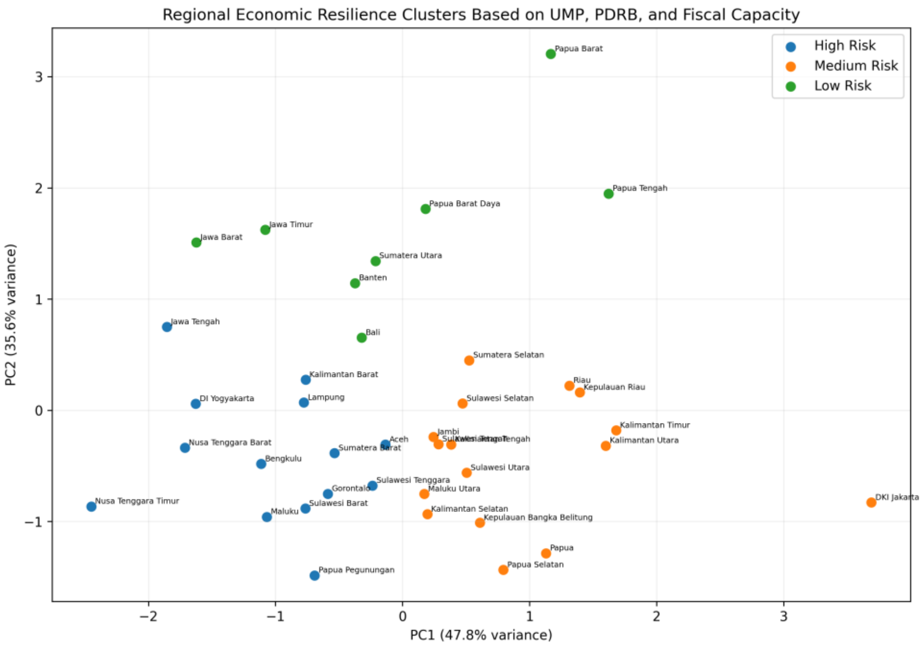

Figure 4. Regional economic-resilience clusters based on UMP, PDRB, and fiscal capacity.
Source: Authors' analysis.

The clustering should not be interpreted as proof that the listed provinces caused national forecast errors. Instead, it provides a transparent prioritization layer for monitoring economic capacity. Provinces in the High-Risk cluster may warrant closer observation of participant composition, payment compliance, and local fiscal conditions, while provinces in stronger clusters provide useful comparison cases.

4.5. Policy Implications: From Prediction to Risk-Informed Planning

The revised results support the use of forecasts as one component of liquidity planning, but forecast-error metrics should not be converted directly into cash-buffer percentages. In particular, a WAPE of 7.71% quantifies average forecast deviation over the 2024 test window; it is not an estimate of a 7.71% revenue shock, solvency margin, or required reserve. The appropriate liquidity buffer should instead be determined through a separate actuarial or financial stress-testing framework that considers the distribution, persistence, and severity of revenue shortfalls.

Operationally, the hybrid model can be used as a short-horizon monitoring tool alongside ARIMA and other benchmarks. Months in which model forecasts diverge materially can trigger additional review of compliance, labor-market conditions, administrative collections, or policy changes. At the regional level, the economic-resilience clusters can support differentiated monitoring intensity without implying causal relationships between regional indicators and national revenue volatility.

5. Conclusion

This study reconstructs the JKN contribution-revenue forecasting workflow around a coherent national monthly series and a chronological evaluation design. The revised hybrid ARIMA-LSTM model achieved a WAPE of 7.71%, compared with 8.18% for ARIMA and 9.98% for LSTM. The hybrid also produced the lowest MAE and MAPE, although ARIMA had a slightly lower RMSE. The evidence therefore supports a modest added value from residual correction rather than universal superiority of the hybrid model.

Descriptive analysis showed a positive association between payment compliance and monthly revenue and a negative association between the mean provincial TPT and revenue, while inflation did not show a meaningful linear association in the study period. A separate K-means regional segmentation further identified provinces with relatively weaker combined UMP, PDRB, and fiscal-capacity profiles. These regional clusters should be interpreted as economic-resilience categories for monitoring, not as causal sources of national forecast error.

Several limitations remain. The monthly modeling sample contains only 48 observations, and the 2024 test period contains 12 observations. A limited number of cumulative source records required transparent transcription correction, and combined January-February YTD amounts were allocated across the two months where a reliable separate January observation was unavailable. The negative R^2 values also indicate that short-term month-to-month variation remains difficult to explain. Future work should incorporate a longer verified monthly history, participant-segment revenue series, richer administrative variables, and formal liquidity stress testing.

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