International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue:4 Volume No.10 July - August – 2026
DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

Forecasting Growth in Vietnam's Trade Sector to 2030: A Multi-Model Time-Series Approach

Nguyen Thi Hong Tu[1*]
[1]*Faculty of Information Technology, Thuyloi University, 175 Tay Son - Kim Lien Ward - Hanoi City, Vietnam*
**Correspondence: Nguyen Thi Hong Tu email: nguyenthihongtu@tlu.edu.vn*

Abstract-Purpose: This study forecasts the growth trajectory of Vietnam's trade sector to 2030 to support policy planning, investment decisions, and market strategy. Method: Six time-series models were implemented and compared in Minitab: Trend Analysis, Decomposition, Moving Average, Single Exponential Smoothing, Double Exponential Smoothing, and Holt-Winters. Model selection followed the lowest MAPE rule, with MSD used as the tie-breaker. Dataset: The study uses ID271 annual data on total retail sales of goods and consumer-service revenue at current prices, divided into retail trade (ID271-1), accommodation and food services (ID271-2), and services and tourism (ID271-3). Results: After a numerical consistency check, Trend Analysis is optimal for retail trade with MAPE = 2.85354%, Trend Analysis is optimal for accommodation and food services with MAPE = 13.00% and MSD = 6,942,315,512, and Decomposition is optimal for services and tourism with MAPE = 10.00% and MSD = 5,059,055,664. Forecasts indicate that the selected sectors increase from 6,442,613 billion VND in 2025 to 8,047,762 billion VND in 2030, equal to 24.91% cumulative growth. Value: The paper contributes an interpretable multi-model forecasting framework, quantitative sectoral evidence, and practical implications for retail, services, tourism, and national trade planning.
Keywords-Growth forecasting; Vietnam trade; time-series modeling; MAPE; Minitab; retail services; tourism forecasting.

I. INTRODUCTION

Vietnam's trade sector is the object of this study. It covers retail trade, accommodation and food services, and services and tourism as measured by total retail sales of goods and consumer-service revenue at current prices. In the period of digital transformation, the sector is affected by e-commerce, logistics modernization, changing consumer behavior, service recovery, and tourism seasonality. Forecasting this sector is therefore a managerial problem as much as a statistical problem, because the results inform inventory planning, retail investment, service capacity, tourism promotion, and national market-development policy.

Recent retail and demand-forecasting studies emphasize that modern trade data are affected by product heterogeneity, promotion effects, structural breaks, seasonality, and external shocks [1]-[4]. Classical statistical methods such as Holt-Winters and ARIMA remain important because they are interpretable and easy to implement for business users, while machine-learning and ensemble methods can improve nonlinear pattern recognition [5]-[9]. For retail goods and services, the literature also indicates that a single forecasting model is rarely best across all product or service categories [10].

Previous studies on Vietnam's commercial activities have mainly described current market conditions or analyzed short-term movements. In contrast, the present study applies a multi-model time-series comparison in Minitab and selects the optimal model for each business sector based on objective error indicators. This addresses three research gaps: the lack of a long-horizon forecast to 2030, the lack of sector-specific model selection, and the lack of a transparent comparison between traditional smoothing, decomposition, and trend models.

The research questions are as follows. RQ1: What is the forecasted growth trend of Vietnam's trade sector to 2030? RQ2: Which time-series model provides the highest accuracy for each sector, as measured by MAPE and MSD? RQ3: How can the forecasting results be used in policy planning and business strategy?

The value of the study is threefold. First, it provides quantitative evidence for national trade-strategy planning. Second, it helps enterprises forecast market demand and align inventory, service capacity, and investment decisions. Third, it provides a replicable methodological framework for other Vietnamese sectors such as import-export, logistics, e-commerce, and provincial tourism services.

The objectives are to construct a database for the three ID271 subsectors, evaluate six time-series models, select the best model using MAPE and MSD, report concrete forecasts to 2030, and discuss strategic implications using the S.W.O.T framework. The remainder of the paper is organized as follows. Section II reviews related studies. Section III presents the proposed research model and mathematical formulation. Section IV reports datasets and results. Section V discusses the findings by S.W.O.T. Section VI concludes the paper and identifies limitations and future research directions.

II. REVIEW OF RELATED LITERATURE

A. Retail, sales, and commercial demand forecasting

The retail-forecasting literature has moved from aggregate trend analysis to more granular demand models. Disaggregated retail forecasting with gradient boosting was shown to manage structural changes, out-of-stock corrections, and product-level effects more flexibly than simple benchmarks [1]. Hybrid systems combining time-series feature engineering and ensemble learning further demonstrate that product-category behavior should be modeled separately rather than forced into a single global pattern [2]. Seasonal retail demand studies also show that methods capable of representing changing seasonal coefficients are useful when data contain small samples and complex seasonal variation [3].

Neural and attention-based demand-forecasting models extend traditional methods by learning nonlinear temporal relationships. The attLSTM framework combines attention and bidirectional LSTM to improve the capture of short-term disturbances, while deep ensemble methods connect forecasting accuracy directly to inventory and order-up-to-level decisions [4], [7]. However, these methods need more data, more tuning, and stronger computational infrastructure than Minitab-based classical models. For enterprises and public agencies that need explainability, Trend Analysis, Decomposition, Moving Average, and Exponential Smoothing remain attractive baselines [5], [6].

B. Tourism, services, and multi-source forecasting

Tourism and service demand are more seasonal and shock-sensitive than basic retail demand. Dynamic spatiotemporal tourism models explicitly incorporate spatial dependence and can support location-based destination planning [11]. Short-video information has recently been used as a demand signal, demonstrating that social-media attention can complement traditional arrivals series [12]. Multi-source frameworks that combine STL decomposition, search-engine data, weather, and holiday indicators also improve daily tourism forecasting and increase interpretability [13].

Recent deep-learning applications such as iTransformer, SARIMAX with Google Trends, and spatial econometric LSTM models show that high-frequency service demand can be improved when historical data are enriched with web search, weather, holiday, and mobility information [14]-[16]. Forecasting daily tourism with multiple factors confirms that temporal heterogeneity matters [17]. Transformer-based, robust decomposition, and duty-free shopping demand models also show that decomposition and multisource data are valuable when service consumption contains irregular events, shopping behavior, and tourism cycles [18]-[20].

C. Research gap

The reviewed studies suggest three gaps for Vietnam trade-sector forecasting. First, many advanced models require large and high-frequency datasets, while public macro-sector data are often annual and aggregated. Second, descriptive reports do not always compare model errors by sector. Third, tourism and service studies often emphasize sophisticated algorithms, but policymakers still need interpretable forecasts with clear error indicators. The present study addresses these gaps by using

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue:4 Volume No.10 July - August – 2026
DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

six transparent time-series models, evaluating them with MAPE, MAD, and MSD, and selecting the most suitable model for each ID271 subsector.

III. PROPOSED RESEARCH MODEL

The proposed model follows a nine-step forecasting pipeline (Figure 1). The model is designed to be simple enough for Minitab implementation and transparent enough for policy interpretation, while still allowing sector-specific model selection.

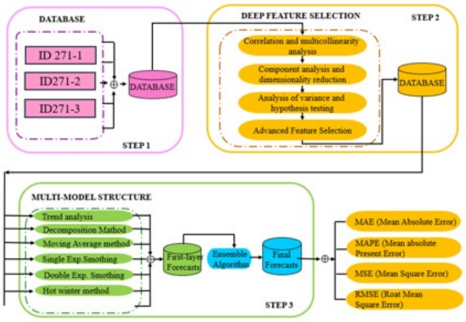

Fig. 1. Proposed multi-model time-series forecasting pipeline

Step 1: Dataset construction. Let $Y_{i,t}$ denote the trade revenue of sector i in year t. Specifically, $i=1$ represents retail trade, $i=2$ represents accommodation and food services, and $i=3$ represents services and tourism. With $t=1,2,\ldots,n$ indicating the years observed, the input data matrix is denoted as $D=\{Y_{i,t}: i=1,2,3;\ t=1\ldots n\}$. This matrix includes the trade revenue of the three sectors over the study period and serves as the input database for the analysis.

Step 2: Data quality and descriptive statistics. For each sector i, descriptive statistics are computed to summarize the main characteristics of the trade revenue data. These statistics include the maximum value, max (Y_i), the minimum value, min (Y_i), the mean value, $\bar{Y}_i=\frac{1}{n}\sum_{t=1}^{n} Y_{i,t}$, and the standard deviation, $\sigma_i=\sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(Y_{i,t}-\bar{Y}_i)^2}$. The maximum and minimum values indicate the range of revenue fluctuations, while the mean represents the average revenue level of each sector over the study period. The standard deviation measures the degree of dispersion around the mean. Together, these descriptive statistics are used to assess whether the dataset is sufficiently stable and appropriate for time-series modeling.

Step 3: Trend Analysis. The linear trend model is $Y_t=a+bt$. Where: a: constant (intersection point at t=0), b: trend coefficient (slope, rate of change over time). This model is suitable when a sector follows a stable long-term path.

Step 4: Decomposition Method. The additive structure is $Y_t=T_t+S_t+e_t$. In this model, T_t represents the trend component, which reflects the long-term movement or general direction of the time series over time. S_t denotes the seasonal component, capturing regular and repeated fluctuations that occur within specific periods, such as months, quarters, or years. Meanwhile, e_t represents the irregular component, which refers to random variations or unexpected changes that cannot be explained by the trend or seasonal patterns. Together, these components help describe the structure of the time-series data and support more accurate analysis and forecasting.

Step 5: Moving Average. For window length k, the next-period forecast is $MA_t=\frac{Y_t+Y_{t-1}+\ldots+Y_{t-n+1}}{n}$. In this moving average model, n represents the number of periods used to calculate the moving average, while Y_t denotes the observed value of the time series at time t. The value of n determines how many consecutive observations are included in the averaging process, helping to smooth short-term fluctuations in the data. Meanwhile, Y_t provides the actual observed data point at each specific time period. Together, these elements are used to estimate the underlying trend of the time series and support more reliable forecasting.

Website: ijetms.in Issue:4 Volume No.10 July - August – 2026
DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

Step 6: Single Exponential Smoothing. The forecast is $F_{t+1}=\alpha Y_t+(1-\alpha)F_t$. In the exponential smoothing model, αrepresents the smoothing coefficient, where $0<\alpha<1$. This coefficient determines the weight assigned to the most recent actual observation in the forecasting process. A higher value of αmakes the forecast more responsive to recent changes, while a lower value produces a smoother forecast. In addition, $Y_t$denotes the actual observed value at time t, and $F_t$represents the forecasted value at time t. These components are used to update forecasts over time by combining actual observations with previous forecast values.

Step 7: Double Exponential Smoothing. Holt smoothing estimates a level $\begin{cases} L_t=\alpha Y_t+(1-\alpha)(L_{t-1}+T_{t-1}) \\ T_t=\beta(L_t-L_{t-1})+(1-\beta)T_{t-1} \\ F_{t+m}=L_t+mT_t \end{cases}$. In Holt's linear trend method, α represents the level smoothing coefficient, while βrepresents the trend smoothing coefficient. The term $L_t$denotes the estimated level of the time series at time t, reflecting the current baseline value after smoothing. Meanwhile, $T_t$refers to the trend slope at time t, which captures the direction and rate of change in the series over time. The parameter $m$indicates the number of periods ahead to be forecasted. Together, these components allow the model to account for both the current level and the underlying trend of the data, thereby improving the accuracy of future forecasts.

Step 8: Holt-Winters Method. For multiplicative seasonality with period s, $\begin{cases} L_t=\alpha\frac{Y_t}{S_{t-s}}+(1-\alpha)(L_{t-1}+T_{t-1}) \\ T_t=\beta(L_t-L_{t-1})+(1-\beta)T_{t-1} \\ S_t=\gamma\frac{Y_t}{L_t}+(1-\gamma)S_{t-s} \\ F_{t+m}=(L_t+mT_t)S_{t-s+m} \end{cases}$. In the Holt-Winters exponential smoothing model, αrepresents the level smoothing coefficient, β represents the trend smoothing coefficient, and γ represents the seasonal smoothing coefficient. These parameters control how strongly the model updates the level, trend, and seasonal components based on recent observations. The parameter $s$denotes the length of the seasonal cycle, such as 4 for quarterly data or 12 for monthly data. In addition, L_t, T_t, and S_t represent the level, trend, and seasonal components at time t, respectively. Together, these components allow the model to capture the current value, the direction of movement, and recurring seasonal patterns in the time series, thereby supporting more accurate forecasting.

Step 9: Error evaluation and model selection. Model accuracy is evaluated using three error measures: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD). MAPE is calculated as $MAPE=\frac{100}{n}\sum|\frac{Y_t-\hat{Y}_t}{Y_t}|$, MAD is calculated as $MAD=\frac{1}{n}\sum|Y_t-\hat{Y}_t|$, and MSD is calculated as $MSD=\frac{1}{n}\sum(Y_t-\hat{Y}_t)^2$. In these formulas, $Y_t$represents the actual observed value, while $\hat{Y}_t$represents the forecasted value at time t. For each sector, the best forecasting model is selected based on the criterion $m_i^*=\arg\min_m MAPE_{i,m}$, meaning that the model with the lowest MAPE is chosen. If two or more models have the same MAPE value, the model with the lowest MSD is selected as the final forecasting model.

IV. RESEARCH RESULTS

This section reports the dataset architecture, descriptive statistics, model-error comparison, selected models, and forecasts to 2030. All monetary values are in billion VND at current prices.

Table 1. Data architecture and descriptive statistics

Dataset	Business sector	Max	Min	Average	Sigma	Assessment
ID271-1	Retail trade	4,928,681	2,403,723	3,615,419	809,923	Accepted
ID271-2	Accommodation and food services	755,823	364,677	529,303	121,398	Accepted

DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

ID271-3	Services and tourism	762,893	403,949	553,544	115,030	Accepted

The descriptive results show that retail trade is the largest subsector, with an average value of 3,615,419 billion VND. Accommodation and food services and services and tourism have lower averages, 529,303 and 553,544 billion VND, respectively, but they are strategically important because they are more exposed to service recovery and tourism cycles.

Table 2. Forecasting-error indicators for ID271

Model	Metric	ID271-1	ID271-2	ID271-3
Trend Analysis	MAPE	2.85354	13	10
	MAD	104,912	61,597	48,768
	MSD	22,017,100,000	6,942,315,512	5,209,606,151
Decomposition	MAPE	2.86950	13	10
	MAD	105,446	61,510	49,223
	MSD	21,314,700,000	6,998,448,191	5,059,055,664
Moving Average	MAPE	11.6033	22.5985	18.5351
	MAD	448,222	120,958	104,372
	MSD	224,660,000,000	16,933,900,000	13,773,900,000
Single Exp. Smoothing	MAPE	6.10482	12	13
	MAD	222,554	66,023	70,025
	MSD	78,965,800,000	8,473,483,438	8,223,587,735
Double Exp. Smoothing	MAPE	3.67569	12	12
	MAD	139,625	62,394	60,225
	MSD	40,698,500,000	8,984,011,106	8,518,216,210
Holt-Winters	MAPE	4.87519	16.2941	13
	MAD	169,880	76,680	66,747
	MSD	44,942,800,000	11,760,600,000	8,650,826,668

A consistency check was performed because the source narrative selected Moving Average for ID271-1, whereas the numerical MAPE table reports Trend Analysis at 2.85354% and Moving Average at 11.6033%. Following the stated rule of selecting the lowest MAPE, this revised paper selects Trend Analysis for ID271-1. For ID271-2, Single and Double Exponential Smoothing report MAPE = 12, but their MSD values are higher than Trend Analysis. Since the original method uses MSD as an additional criterion when MAPE is equal or near-equal, Trend Analysis is retained for ID271-2. For ID271-3, Trend Analysis and Decomposition both show MAPE = 10, and Decomposition is selected because its MSD = 5,059,055,664 is lower than the Trend Analysis MSD = 5,209,606,151.

Table 3. Selected models and 2030 forecasting results

Sector	Selected model	Selection criterion	2025 forecast	2030 forecast	Cumulative growth	CAGR
ID271-1 Retail trade	Trend Analysis	MAPE = 2.85354%	5,059,022	6,371,389	25.94%	4.72%
ID271-2 Accommodation and food services	Trend Analysis	MSD = 6,942,315,512	681,547	819,951	20.31%	3.77%
ID271-3 Services and tourism	Decomposition	MSD = 5,059,055,664	702,044	856,422	21.99%	4.06%
Aggregate selected sectors	-	-	6,442,613	8,047,762	24.91%	4.55%

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue:4 Volume No.10 July - August – 2026
DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

The quantitative results indicate that retail trade remains the dominant component of Vietnam's trade sector. Under the selected Trend Analysis model, retail trade increases from 5,059,022 billion VND in 2025 to 6,371,389 billion VND in 2030, equal to 25.94% cumulative growth. Accommodation and food services increase from 681,547 to 819,951 billion VND, while services and tourism increase from 702,044 to 856,422 billion VND. The aggregate value of the three selected forecasts rises by 1,605,149 billion VND between 2025 and 2030.

Table 4. Forecast values from the selected models, 2025-2030

Year	**ID271-1 Retail trade: Trend Analysis**	**ID271-2 Accommodation and food services: Trend Analysis**	**ID271-3 Services and tourism: Decomposition**
2025	5,059,022	681,547	702,044
2026	5,321,495	709,228	742,792
2027	5,583,969	736,909	757,877
2028	5,846,442	764,590	799,607
2029	6,108,915	792,271	813,710
2030	6,371,389	819,951	856,422

V. DISCUSSION

The results demonstrate that Vietnam's trade-sector components do not share the same data structure. Retail trade follows a stable long-run trend and is therefore well represented by Trend Analysis. Accommodation and food services also show a recoverable upward trend. Services and tourism require Decomposition because seasonal and cyclical movements are important. This supports the argument that model selection should be sector-specific rather than applied uniformly across the whole trade sector.

A. S.W.O.T comparison with previous studies

Table 5. S.W.O.T discussion and comparison with previous research

S.W.O.T element	**Comparison with previous studies**	**Implication for this research**
Strengths	Compared with machine-learning retail studies [1], [2], [4], this paper is more interpretable and easier to reproduce in Minitab. Its ID271-1 MAPE of 2.85354% is also competitive with recent retail studies that report MAPE values around 3%-4% in different datasets [6].	A transparent multi-model comparison can support government and enterprise users who need explainable forecasts.
Weaknesses	Compared with ensemble and deep-learning studies using external factors [7]-[9], the present study uses univariate annual data and does not include GDP, inflation, online search, consumer sentiment, or policy-shock variables.	Forecasts are reliable for baseline planning but should not be interpreted as shock-adjusted forecasts.
Opportunities	Tourism and service studies show that decomposition, search data, weather, holiday, and social-media information can improve demand prediction [11]-[16].	Future Vietnam forecasts can integrate monthly data, Google Trends, e-commerce indicators, and provincial tourism arrivals.
Threats	Recent tourism-demand papers emphasize shocks, events, spatial effects, and behavior change [17]-[20].	Pandemics, trade restrictions, inflation, supply-chain disruption, and geopolitical changes may cause deviations from the baseline trend.

DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

B. Managerial and policy implications

For retail trade, the projected 2030 value of 6,371,389 billion VND suggests a need for inventory optimization, digital payment infrastructure, logistics improvement, and modern retail-channel expansion. Because the trend is stable, business strategies should prioritize operational efficiency, supply-chain coordination, and demand-responsive assortment planning.

For accommodation and food services, the 2030 forecast of 819,951 billion VND suggests a continued recovery path. Firms should invest in service quality, workforce training, digital booking systems, and destination-linked culinary products. Public policy should focus on service standards, local tourism linkages, and support for small and medium enterprises.

For services and tourism, the 2030 forecast of 856,422 billion VND and the superiority of Decomposition indicate that seasonal resource allocation is essential. Tourism agencies and enterprises should schedule marketing campaigns by peak season, manage transport and accommodation capacity, and design off-season promotions to reduce volatility.

VI. CONCLUSION

This study provides value by transforming descriptive trade-sector information into an interpretable quantitative forecasting framework. It applies six Minitab time-series models, compares MAPE, MAD, and MSD, and selects the most suitable model for each ID271 subsector. The framework can be used by policymakers, retailers, service providers, and tourism managers to support long-term planning to 2030.

The main results are concrete. Retail trade is forecast to grow from 5,059,022 billion VND in 2025 to 6,371,389 billion VND in 2030, with MAPE = 2.85354% and CAGR = 4.72%. Accommodation and food services are forecast to grow from 681,547 to 819,951 billion VND, with MSD = 6,942,315,512 and CAGR = 3.77%. Services and tourism are forecast to grow from 702,044 to 856,422 billion VND, with MSD = 5,059,055,664 and CAGR = 4.06%. In total, the selected sectors increase by 24.91% from 2025 to 2030.

The study has several limitations. It uses univariate annual data, which limits its ability to capture monthly seasonality and external drivers. It does not explicitly model inflation, GDP, household consumption, international arrivals, e-commerce adoption, exchange rates, or unexpected shocks such as pandemics and trade-policy changes. Some advanced models also require longer and higher-frequency datasets for robust estimation.

Future research should extend the dataset to monthly or quarterly frequency, incorporate macroeconomic and digital-commerce variables, and compare the current Minitab-based framework with ARIMAX, VAR, Prophet, Random Forest, XGBoost, LSTM, Transformer, and hybrid decomposition-ensemble models. A real-time dashboard can also be developed to update forecasts automatically as new statistical data become available.

Acknowledgments: The authors thank Thuyloi University, Vietnam, for academic guidance and support.

Data availability: The study uses the ID271 data architecture and Minitab forecast outputs provided in the source document. Additional raw data files are not attached to this article.

REFERENCES

[1] L. A. C. G. Andrade and C. B. Cunha, "Disaggregated retail forecasting: A gradient boosting approach," Applied Soft Computing, vol. 141, Art. no. 110283, 2023, doi: 10.1016/j.asoc.2023.110283.

[2] S. Mejia and J. Aguilar, "A demand forecasting system of product categories defined by their time series using a hybrid approach of ensemble learning with feature engineering," Computing, vol. 106, pp. 3945-3965, 2024, doi: 10.1007/s00607-024-01320-y.

[3] L. Ye, N. Xie, J. E. Boylan, and Z. Shang, "Forecasting seasonal demand for retail: A Fourier time-varying grey model," International Journal of Forecasting, vol. 40, no. 4, pp. 1467-1485, 2024, doi: 10.1016/j.ijforecast.2023.12.006.

DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

[4] L. Cui, Y. Chen, J. Deng, and Z. Han, "A novel attLSTM framework combining the attention mechanism and bidirectional LSTM for demand forecasting," Expert Systems with Applications, vol. 254, Art. no. 124409, 2024, doi: 10.1016/j.eswa.2024.124409.
[5] L. Kumar, S. Khedlekar, and U. K. Khedlekar, "A comparative assessment of Holt Winter exponential smoothing and autoregressive integrated moving average for inventory optimization in supply chains," Supply Chain Analytics, Art. no. 100084, 2024, doi: 10.1016/j.sca.2024.100084.
[6] M. N. Ince and C. Tasdemir, "Forecasting retail sales for furniture and furnishing items through the employment of multiple linear regression and Holt-Winters models," Systems, vol. 12, no. 6, Art. no. 219, 2024, doi: 10.3390/systems12060219.
[7] M. Seyedan, F. Mafakheri, and C. Wang, "Order-up-to-level inventory optimization model using time-series demand forecasting with ensemble deep learning," Supply Chain Analytics, vol. 3, Art. no. 100024, 2023, doi: 10.1016/j.sca.2023.100024.
[8] Z. Wu, X. Chen, and Z. Gao, "Bayesian non-parametric method for decision support: Forecasting online product sales," Decision Support Systems, vol. 174, Art. no. 114019, 2023, doi: 10.1016/j.dss.2023.114019.
[9] X. Song, L. Deng, H. Wang, Y. Zhang, Y. He, and W. Cao, "Deep learning-based time series forecasting," Artificial Intelligence Review, vol. 58, Art. no. 23, 2025, doi: 10.1007/s10462-024-10989-8.
[10] K. Swaminathan and R. Venkitasubramony, "Demand forecasting for fashion products: A systematic review," International Journal of Forecasting, vol. 40, no. 1, pp. 247-267, 2024, doi: 10.1016/j.ijforecast.2023.02.005.
[11] M. Pan, Z. Liao, Z. Wang, C. Ren, Z. Xing, and W. Li, "Tourism forecasting: A dynamic spatiotemporal model," Annals of Tourism Research, vol. 110, Art. no. 103871, 2025, doi: 10.1016/j.annals.2024.103871.
[12] M. Hu, N. Dong, and F. Hu, "Tourism demand forecasting using short video information," Annals of Tourism Research, vol. 109, Art. no. 103838, 2024, doi: 10.1016/j.annals.2024.103838.
[13] Z. Zhang, Z. Xu, and W. Yu, "Tourism demand forecasting with multi-source data: A hybrid model incorporating seasonal-trend decomposition," Annals of Operations Research, 2025, doi: 10.1007/s10479-025-06832-0.
[14] J. Huang and C. Zhang, "Daily tourism demand forecasting with the iTransformer model," Sustainability, vol. 16, no. 23, Art. no. 10678, 2024, doi: 10.3390/su162310678.
[15] G.-C. Lee, "A data-driven approach to tourism demand forecasting: Integrating web search data into a SARIMAX model," Data, vol. 10, no. 5, Art. no. 73, 2025, doi: 10.3390/data10050073.
[16] J. Ma, "Demand forecasting of smart tourism integrating spatial metrology and deep learning," Scientific Reports, vol. 15, Art. no. 42646, 2025, doi: 10.1038/s41598-025-26830-3.
[17] S. Xu, Y. Liu, and C. Jin, "Forecasting daily tourism demand with multiple factors," Annals of Tourism Research, vol. 103, Art. no. 103675, 2023, doi: 10.1016/j.annals.2023.103675.
[18] X. Li, Y. Xu, R. Law, and S. Wang, "Enhancing tourism demand forecasting with a transformer-based framework," Annals of Tourism Research, vol. 107, Art. no. 103791, 2024, doi: 10.1016/j.annals.2024.103791.
[19] X. Li, X. Zhang, C. Zhang, and S. Wang, "Forecasting tourism demand with a novel robust decomposition and ensemble framework," Expert Systems with Applications, vol. 236, Art. no. 121388, 2024, doi: 10.1016/j.eswa.2023.121388.
[20] D. Zhang, P. Wu, C. Wu, and E. W. T. Ngai, "Forecasting duty-free shopping demand with multisource data: A deep learning approach," Annals of Operations Research, vol. 339, no. 1-2, pp. 861-887, 2024, doi: 10.1007/s10479-024-05830-y.

APPENDIX A. FULL FORECAST TABLES FROM THE SIX MODELS

The appendix preserves the six-model forecast outputs from the source file for traceability. The main text reports the selected models only.

DOI:10.46647/ijetms.2026.v10i04.002 ISSN: 2581-4621

Table A1. Forecasting results for ID271-1: Retail trade

Year	Trend	Decomp.	Moving Avg.	Single ES	Double ES	Holt-Winters
2025	5,059,022	5,040,684	4,740,892	5,099,711	5,178,641	5,014,952
2026	5,321,495	5,331,888	4,740,892	5,099,711	5,472,916	5,485,545
2027	5,583,969	5,562,845	4,740,892	5,099,711	5,767,191	5,550,706
2028	5,846,442	5,857,016	4,740,892	5,099,711	6,061,465	6,041,856
2029	6,108,915	6,085,005	4,740,892	5,099,711	6,355,740	6,086,459
2030	6,371,389	6,382,143	4,740,892	5,099,711	6,650,015	6,598,168

Table A2. Forecasting results for ID271-2: Accommodation and food services

Year	Trend	Decomp.	Moving Avg.	Single ES	Double ES	Holt-Winters
2025	681,547	684,737	712,594	807,238	848,963	689,570
2026	709,228	707,721	712,594	807,238	911,628	768,648
2027	736,909	740,556	712,594	807,238	974,292	755,432
2028	764,590	763,155	712,594	807,238	1,036,957	838,716
2029	792,271	796,375	712,594	807,238	1,099,621	821,293
2030	819,951	818,588	712,594	807,238	1,162,286	908,784

Table A3. Forecasting results for ID271-3: Services and tourism

Year	Trend	Decomp.	Moving Avg.	Single ES	Double ES	Holt-Winters
2025	710,271	702,044	727,085	772,705	815,017	707,967
2026	738,767	742,792	727,085	772,705	867,288	796,326
2027	767,262	757,877	727,085	772,705	919,559	772,846
2028	795,758	799,607	727,085	772,705	971,830	866,105
2029	824,254	813,710	727,085	772,705	1,024,100	837,726
2030	852,750	856,422	727,085	772,705	1,076,371	936,885