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Modeling the Dynamic Impact of TikTok Advertising Expenditure on Skincare Product Demand: Evidence from Time Series Analysis

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ABSTRACT

This study examines the dynamic impact of TikTok advertising expenditure on skincare product demand using a time-series framework. The objective is to evaluate whether incorporating digital advertising spending as an exogenous variable improves sales forecasting accuracy on social commerce platforms. Monthly secondary data from Company X, covering shampoo and cream products sold on TikTok from October 2024 to October 2025, were analyzed. The study compares ARIMA, ARIMA with Trend, and ARIMAX models. Stationarity was tested using the Augmented Dickey–Fuller test, while model selection was based on AIC, MSE, RMSE, and MAPE. The results reveal heterogeneous demand characteristics across products. Shampoo demand shows strong persistence and relatively stable patterns, with advertising expenditure having a positive but limited incremental effect on forecasting accuracy. In contrast, cream demand is highly sensitive to advertising intensity. The ARIMAX model significantly outperforms alternative models for cream products, producing substantially lower forecast errors. These findings indicate that promotional elasticity differs across product categories. Managerially, the results suggest that promotion-driven products require tighter integration between marketing expenditure planning and operational forecasting, while habitual products may rely more on historical demand patterns. This study contributes to digital marketing and forecasting literature by empirically demonstrating the product-specific effectiveness of social media advertising within a dynamic time-series context.

KATA KUNCI

TikTok Shop, Periklanan, Deret Waktu, Peramalan, E-*commerce*

ABSTRAK

Penelitian ini menganalisis dampak dinamis pengeluaran iklan TikTok terhadap permintaan produk perawatan kulit dengan menggunakan pendekatan time-series. Tujuan penelitian adalah mengevaluasi apakah integrasi belanja iklan digital sebagai variabel eksogen dapat meningkatkan akurasi peramalan penjualan pada platform *social commerce*. Data sekunder bulanan dari Company X yang mencakup produk sampo dan krim di TikTok periode Oktober 2024 hingga Oktober 2025 dianalisis menggunakan model ARIMA, ARIMA dengan *Trend*, dan ARIMAX. Uji stasioneritas dilakukan dengan Augmented Dickey–Fuller, sedangkan pemilihan model didasarkan pada AIC, MSE, RMSE, dan MAPE. Hasil penelitian menunjukkan perbedaan karakteristik permintaan antar produk. Permintaan sampo relatif stabil dengan ketergantungan tinggi pada periode sebelumnya, dan pengaruh iklan bersifat positif namun tidak secara signifikan meningkatkan akurasi prediksi. Sebaliknya, permintaan krim sangat sensitif terhadap intensitas promosi digital. Model ARIMAX memberikan kinerja terbaik untuk produk krim dengan tingkat kesalahan prediksi yang jauh lebih rendah dibandingkan model lainnya. Temuan ini mengindikasikan bahwa elastisitas promosi bersifat spesifik terhadap kategori produk. Secara manajerial, produk yang bersifat *promotion-driven* memerlukan integrasi yang lebih erat antara perencanaan anggaran pemasaran dan peramalan operasional, sedangkan produk *habitual* dapat lebih mengandalkan pola historis. Penelitian ini berkontribusi pada literatur pemasaran digital dan peramalan permintaan melalui bukti empiris berbasis data *time-series*.

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1. Introduction

1.1. Research Background

The Pharma industry is evolving rapidly, and with this, the way consumers interact with it is changing enormously. Pharmaceutical products, including medicines, are also expected to be in high demand with the growth of Indonesia's middle class as a sector comprising multi-stakeholders [1]. Such developments highlight the importance of flexible management approaches to adapt to changing market demands and escalating competition.

Likewise, due to the competition within the wider cosmetic industry and thus also in the skincare sub-industry, constant marketing innovation is also required to gain traction between consumers. Now social media, and especially TikTok, is one of the main places where skincare products are promoted. The demand for cosmetic products around the globe has increased greatly in recent years owing to remarkable development of industry [2]. Through creative video content, partnerships with beauty influencers and the ability to drive consumer decisions, TikTok was one of the biggest marketing platforms within not just this space but also skincare overall. Examples from empirical data show how TikTok has an impact on consumer behavior with its engaging content and recommendations by influential persons [3].

Currently, Indonesians spend an average of more than 3 hours a day on social media, making these platforms part of lifestyle and consumer decision-making stages. Research said that the rise of digital public figures who offer personalized and interactive product recommendations has enhanced social media's impact on consumer behavior [4]. In addition, based on the latest social commerce research 40% of Indonesian consumers often transact on social media and reaffirming its position as an important and strategic transaction channel among the community.

In digital marketing, TikTok advertising expenditure is a significant factor affecting product demand. Studies in digital marketing indicate that methods like targeted advertising, brand awareness campaigns, and emotionally impactful content enhance the purchase decision effectiveness [5]. Information seeking and purchasing have been revolutionized by the digitalization of consumer behavior, resulting in a rise in exposure to promotional content that induces perceptions, preferences and decisions. An international study shows that social media advertising has a positive relationship with purchasing decisions, with content components such as interactivity, relevance, and the ability to build consumer engagement contributing to consumers' purchase decisions [6].

Sales models for products like skincare are closely related to the relationship between digital marketing and consumer habits; as one grows in efficacy so does another. Digital advertising has a well-documented impact on social media users, resulting in more interactions which subsequently lead to higher purchase interest and thus greater sales volumes [7]. Moreover, seasonality has a high impact on the purchasing behavior of consumers since it drives them to spend larger amounts during specific periods because of trends they follow, promotional campaigns, or cultural events like holidays. Indeed, empirical analyses verify that marketing campaigns and ads occurring during such times magnify seasonal impacts bringing significant but transient spikes in demand. This dynamic accounts for the pronounced fluctuations in consumer demand for products such as skincare [8], [9].

According to Tempo News, growing demand was driven by the use of digital platforms, where TikTok Shop Indonesia recorded a 40% increase in sales during Ramadan 2025 [10]. This highlights how successful TikTok's digital strategy and promotion efforts have been to drive transaction volumes and consumer demand during these seasonal events. Changes in how consumers shop have also transformed the way they process information and evaluation. Consumers previously relied on in-store interactions with sales attendants for recommendations, but now they are faced with a practically limitless amount of product information online — descriptions, user reviews, price comparisons and constant promotions. Recent research also said that the live streaming feature of TikTok influences behavioral intentions, which can be further strengthened by the social presence of other users [11].

TikTok has become one of the social networks with strong advertising and content features, powerful recommendation algorithms. Studies that focus on social media and purchasing behavior as a whole also indicate how digital advertising content affects consumers, especially in strengthening their commitment to purchase products and market demand [12]. When shopping online, consumers receive a lot of product information which can induce fast-shopping; however, it may also lead to stress and frustration that causes decreased intention to continue shopping [13]. Therefore, it is important to empirically examine the relationship between TikTok ad spend and skincare product demand, especially in the context of time and seasonality. Time series models and model effectiveness comparisons can provide insights into how consumer buying behavior variables and digital promotion strategies actively influence product demand patterns.

While many studies have investigated the effects of social media marketing on consumers' interest in purchasing and purchase decision making, most studies continue to examine perceptual and behavioral variables that are captured by survey or cross-sectional methods. However, dynamic measurement of how social media advertising spending influences real-time demand remains under-explored empirically. Additionally, in sales forecasting literature most time-series models (ARIMA and exponential smoothing) are utilizing historical patterns of sales without considering marketing variables as exogenous factors influencing the behavior of demand. Indeed, when dealing with digital channels heavily impacted by promotional intensity like social commerce, neglecting ad spending variables in modeling can create suboptimal solutions. In addition, despite the fact that TikTok Shop has emerged as a popular social commerce platform, there is still a relative dearth of empirical studies using actual sales data to investigate how demand for products responds to TikTok ad spend over time.

We expect this work to make both empirical and theoretical contributions. From an empirical standpoint, the research outcomes have a goal to assist business practitioners and managers in devising more effective strategies through their identification of the key elements that drive consumer actions on the studied territory, to be able to create more accurate and data-driven action plans. According to theory, the study contributes to a better understanding of management and marketing aspects, enriches the existing literature regarding variables under analysis, and sets a background for future research with more complex models and approaches. Thus, this study aims to model the relationship between skincare product demand on the TikTok Shop platform with TikTok advertising spending as an exogenous variable in a time-series framework while assessing multiple forecasting methods performance.

1.2. Literature Review

1.2.1. Sales Forecasting

Sales forecasting is a systematic process of predicting future sales values using historical data pattern. If done correctly, forecasting will help managerial decision making about what we plan to do in the future and as a guide to know how (especially in terms of sales result) their goals have not been reached. Apart from being a tool for prediction, sales forecasting can also be the basis for data structure analysis and product demand dynamics [14]. Accordingly, selecting an appropriate method for sales forecasting can become decisive in order to obtain reliable and relevant estimates of the sales figures.

A study mention that sales forecasting refers to the process of estimating future sales, contributing significantly to tactical planning and efficient resource allocation [15]. In an increasingly competitive business environment, demand forecasting accuracy is critical to ensure that inventory management, supply chain optimization and financial planning is done correctly while also keeping buyers happy.

1.2.2. Time Series

A very common method for sales forecasting is the time series approach since it can catch temporal dependencies between periods. This model uses historical sales data and locates patterns in recurring trends, spikes, seasonality, etc. Actual sales data often has quite complex seasonal patterns and trends, thus time-series model would suit better to analyze the performance of sales and forecast the demand [16].

Time series modeling is a significant area of academic research and has applications across sectors including climate, biology, medicine, retail and finance. Traditional methods include autoregressive (AR) and exponential smoothing parametric models, and structural models. However, as more data and computing power have become available, data-driven machine learning methods are now an essential component of modern time series forecasting model development [17].

1.2.3. ARIMA Model

ARIMA (Autoregressive Integrated Moving Average) is a classical statistical model that has been used widely for sales forecasting. We combine autoregressive (AR), differencing (I) and moving-average (MA) components in a single model to describe the correlation between current and past values of sales. ARIMA can be considered a sales prediction model as it provides an optimum method for modeling both stationary and non-stationary data [18]. Because it is frequently used as a baseline before more complex models are implemented, this model serves as useful comparative analysis to sales forecasting.

1.2.4. ARIMA Model with Trend

ARIMA with Trend is another popular sales forecast method, but it only works well when you have data that shows a long-term trend. This model disentangles the level and trend components well, so that the analysis results are consistently reflected in the forecast direction of data. It will be successful at forecasting long-term trends with smooth predictions, and not overly reactive to abrupt changes [19].

1.2.5. ARIMAX Model and Exogenous Variables

This model is an extension of the basic ARIMA to include outside variables that presumed to affect the dependent variable. It is well known that exogenous variables including but not limiting to advertising spend, promotions or economic variables significantly impact demand. It is stated that for sales data driven by marketing activities, this model can lead to more stable and accurate results [20].

1.2.6. SME, RMSE, and MAPE Model

This step aims to assess the accuracy of our predictions, so we can test how much it reflects the real data. Statistical error measurement methods, e.g. Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) are the typical adopted for this forecasting. With MAPE being the most common type of analysis in general research, however combining multiple error measures can provide a more inclusive and fair performance metrics [21].

1.3. Research Contributions

This research contributes to the field by developing a new forecasting model that uses digital advertising spending as an external predictor in its ARIMAX dynamic time-series forecasting. As from the literature, there is lack of studies that indicates how changes in advertising expenditure over time will affect sales outcomes on TikTok Shop and similar social commerce applications, these findings also explore whether consumer purchasing behaviour is modified due to advertisements shared on social media platforms as well as their product evaluations.

2. Research Method

This research uses a quantitative, time-series approach to model, compare, and predict sales patterns of skincare products on the TikTok platform, using historical data. The data used in this study is secondary data from Company X in the form of:

a. Sales data for Company X's shampoo and cream products on TikTok digital platform

b. Advertising spend data for each product on TikTok digital platform

The data for this study were compiled into a monthly time series over one year, from October 2024 to October 2025, with sales as the dependent variable and advertising spend as the exogenous variable in the ARIMAX model.

3. Result and Discussion

3.1. Data of Shampoo

Based on Figure 1, it can be seen that from October 2024 to October 2025, there was an overall upward trend in sales. At the beginning of the period, sales were still very low, then gradually increased until reaching their peak towards the end of the period. There was an extreme surge in sales around the end of September/early October 2025, with sales reaching almost 100 units. Overall, shampoo sales gradually increase from 2024 to mid-2025, with each yearly pattern reflecting a seasonal fluctuation. At the end of September 2025, there was an exceptional spike which could be due to a huge promotional campaign or viral thing. Sales came down from the surge, but stabilized at a higher level than before; this implies an adjustment in medium-term demand.

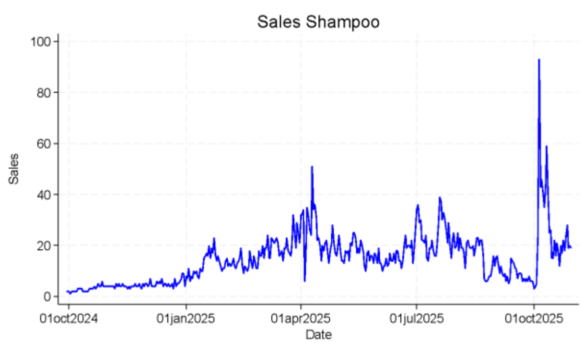

Figure 1. Shampoo Sales

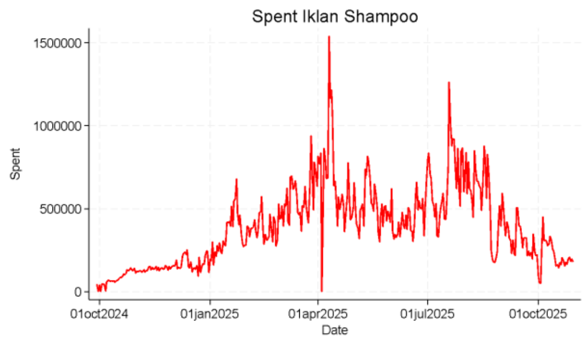

Figure 2. Shampoo Advertising Expenditure

The chart in Figure 2 depicts a monthly promotional spending on hair shampoo from 2024 October to October 2025. On the whole there is growth in advertising spend over the period, with a very large peak around March–April 2025 followed by slow decline until the end of the period. Advertising spending for shampoo shows a gradual increase from October 2024 to early 2025, then reaches a sharp peak in March–April 2025, indicating a large-scale marketing campaign. After the peak, advertising spending remained high, with intense fluctuations during the second and third quarters of 2025, indicating an active and responsive promotional strategy. Starting in August 2025, advertising spending gradually declined, signaling the end of the intensive promotional phase and a shift to a more stable and controlled marketing phase.

3.1.1. Stationarity Testing

Table 1 shows the results of the ADF test of the variables used in the study. Based on Table 1, the variables have p-values < 0.05, indicating that the variables are stationary at I(0), so there is no need to differentiate the data.

Table 1. Stationarity Test Table

Variable	Level I (0)	
	Statistic	p-value
Sales Shampoo	-4.339	0.0004
Ad Spent Shampoo	-7.734	0.0004

3.1.2. ACF and PACF Shampoo

The ACF graph on Figure 3 shows the correlation between the ln_sales_shampoo value and its past values at various lag times. This ACF graph is used to understand time dependency patterns and help determine the ARIMA time-series model. The ln_sales_shampoo data shows strong and slowly decreasing autocorrelation, indicating long-term dependence across periods. This pattern is consistent with the AR (autoregressive) process and indicates that sales are greatly influenced by sales in the previous period.

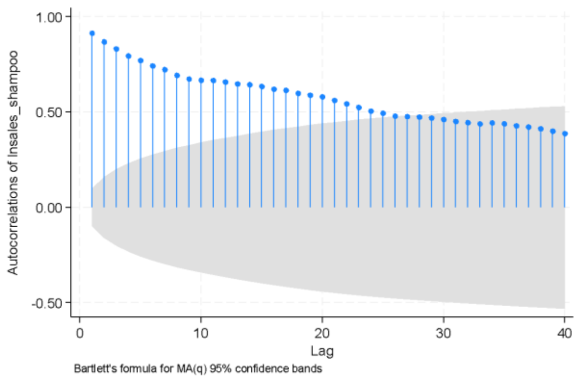

Figure 3. ACF Graph

The PACF graph on Figure 4 shows the partial correlation between ln_sales_shampoo and values from previous periods, after controlling for the effects of other lags. This PACF graph is used to identify the order of autoregressive components in the ARIMA model. In the graph, there is a very significant spike at lag 1, while the subsequent lags fall within the confidence limits and are insignificant. This pattern indicates that the main influence on current sales values comes from the previous period, and there are no strong partial relationships at more distant lags.

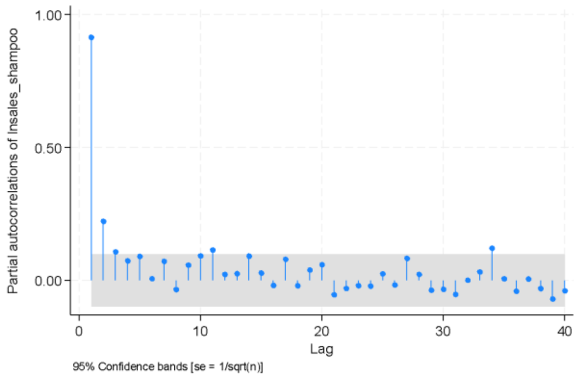

Figure 4. PACF Graph

3.1.3. Determining the Best ARIMA Model

Based on Table 2, which shows the results of testing several ARIMA models, all models have p-values of 0.000, indicating that the parameters in each model are statistically significant and suitable for use. Hence, the choice of the best model is based on goodness-of-fit measures with an emphasis on AIC (Akaike Information Criterion). In ARIMA modeling, the best model is the one with the smallest AIC value, as it indicates the best balance between model complexity and data explanatory power. ARIMA(3,0,1) model has the lowest AIC = 143.541 based on the values in this table. Hence ARIMA(3,0,1) becomes the best model since it finds an optimal accuracy and keeps explaining historical data features properly.

Table 2. ARIMA Model Table

ARIMA Model	Log Likelihood	p-value	AIC
ARIMA (1,0,1)	-70.827	0.000	149.655
ARIMA (2,0,1)	-67.151	0.000	144.301
ARIMA (1,0,2)	-69.241	0.000	148.482
ARIMA (3,0,1)	-65.770	0.000	143.541
ARIMA (3,0,2)	-65.724	0.000	145.448
ARIMA (3,0,3)	-65.012	0.000	146.025

3.1.4. Forecasting Model

The ARIMA estimation results on Table 3 show that the ln_sales_shampoo value is significantly influenced by the values of the previous three periods, with the strongest influence coming from the previous period (AR(1) = 1.552, $p < 0.001$). The influence of the two previous periods is negative and significant, describing a pattern of correction or short-term oscillation in the data (AR(2) = -0.458, $p < 0.001$), while the influence of the third lag is relatively weak and insignificant at the 5% level. The MA(1) component is also significant and negative (-0.889, $p < 0.001$), indicating that shocks in the previous period provide a strong correction to the current value. Overall, the very large and significant chi-square value indicates that the model is able to explain the data variation well.

Table 3. ARIMA (3,0,1) Modeling Table

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
Const (μ)	2.159	0.5483873	3.94	0.000
AR (1)	1.552	0.0583064	26.63	0.000
AR (2)	-0.458	0.0588534	-7.79	0.000
AR (3)	-0.096	0.0558603	-1.72	0.085
MA (1)	-0.889	0.0561225	-15.86	0.000
Log Likelihood				-65.770
Chi-square				307,592.090
p-value				0.000

The ARIMA with Trend estimation results on Table 4 show that ln_sales_shampoo is significantly influenced by the values from the previous three periods. The greatest influence comes from the previous period, as indicated by the AR(1) coefficient = 1.545 ($p < 0.001$), which describes a very strong dependence between time periods. The lag of two periods has a negative and significant effect (AR(2) = -0.454, $p < 0.001$), indicating a short-term correction mechanism in the data, while the lag of three periods has a relatively small and insignificant effect at the 5% level (AR(3) = -0.095, $p = 0.089$). The MA(1) component is also significant and negative (-0.892, $p < 0.001$), indicating that shocks in the previous period have a strong corrective effect on current values. In addition, the model shows an upward trend over time, reflected in the trend coefficient of 0.0051 ($p = 0.004$), indicating that ln_sales_shampoo exhibits small but significant growth over time. Overall, the very high and significant chi-square value confirms that the model has a strong ability to explain the variation in time-series data.

Table 4. ARIMA Modeling with Trend Table

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
Const (μ)	1.2946590	0.4668426	2.77	0.006
Trend	0.0050720	0.0017729	2.86	
AR (1)	1.5445430	0.0710146	21.75	0.004
AR (2)	-0.4541044	0.0651602	-6.97	0.000
AR (3)	-0.0954898	0.0562350	-1.70	0.089
MA (1)	-0.8920380	0.0661004	-13.50	0.000
Log Likelihood				-63.26718
Chi-square				132,228.55000
p-value				0.0000

3.1.5. White Noise Test

The white noise test of the ARIMA (3,0,1) residual model produced a statistical value of 23.7271 with a p-value = 0.9808. This indicates that the residuals are white noise, so the residuals do not have an autocorrelation pattern.

3.1.6. Forecasting

Based on the ARIMA (3,0,1) forecasting graph on Figure 5, the model shows a strong ability to capture the historical pattern of shampoo sales, as evidenced by the prediction line that almost overlaps with the actual data during the in-sample period. After entering the forecast period, the model projects a gradual decline in sales, followed by stabilization near the long-term average. This downward trend in the prediction pattern arises because the ARIMA model used does not include seasonal factors, so it does not capture any periodic fluctuations that may be present in the data. In addition, the surge in sales at the end of the actual period is not carried over by the model, because ARIMA naturally returns to the average trend after extreme values. Overall, these results show that the model provides a conservative and stable long-term picture, but for more realistic predictions, especially when seasonal patterns or external variable influences are present, the ARIMAX model may be a more appropriate choice.

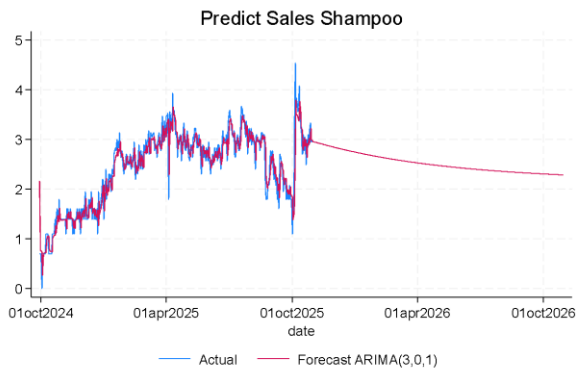

Figure 5. ARIMA (3,0,1) Forecasting

According to the ARIMA with Trend prediction results on Figure 6, the model has high efficacy in fitting historical shampoo sales trend throughout the in-sample period, shown by the fact that all of the forecasted points almost coincide directly with recorded data. Entering into the forecast period though, model predicts a sales trend continuing an upwards increase. The reason is that ARIMA with Trend captures the linear trend component in historical data, and the model assumes that the increasing behavior will continue toward the future. While the non-trend ARIMA generates mean-reverting predictions, adding a Trend component to the ARIMA model generates predictions that continue on an upward trajectory in line with detected trend. And extreme spikes at the end of the actual data affect where the start point is for trend, raising and steepening what we see as prediction line. ARIMA with Trend Conclusion: Overall, ARIMA with Trend results are optimistic for future sales growth; however, they should be interpreted regarding whether this continually-increasing trend pattern is realistic or whether there are seasonal and/or additional external factors that have not yet been included in the analysis.

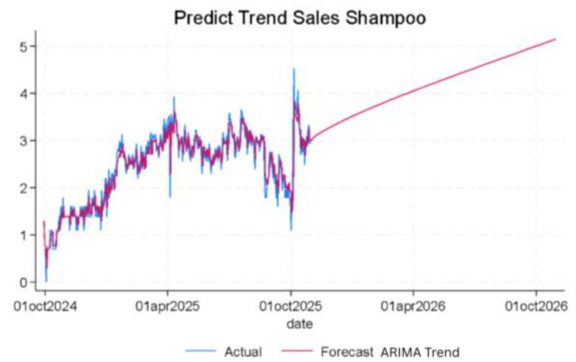

Figure 6. ARIMA with Trend Forecasting

The comparison graph on Figure 7 shows a very clear difference between the results of ARIMA (3,0,1) forecasting and ARIMA with Trend methods. During the historical period, both models followed the actual pattern quite well, as evidenced by the prediction lines that moved almost in parallel with the actual data. However, after entering the forecasting period, the direction of the two models' predictions differed significantly. The ARIMA model projects a gradual decline in sales, followed by stabilization at a lower level, reflecting its non-seasonal nature and returning to the long-term average. In contrast, an ARIMA with Trend model predicts a consistent increase in sales, as it captures the trend component assumed to continue into the future. This difference indicates that ARIMA provides a more conservative projection, while Trend tends to be more optimistic. Therefore, the selection of the ideal model must consider the actual characteristics of the data, whether there is a continuous upward trend or whether the data are more volatile and tend to return to the average.

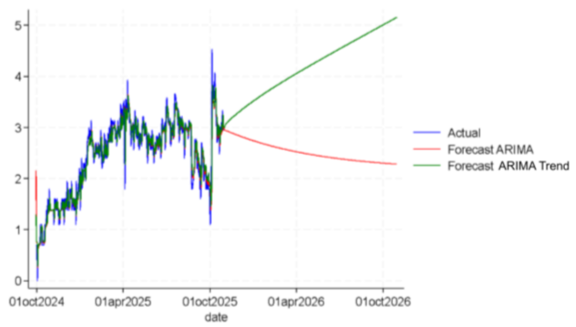

Figure 7. ARIMA (3,0,1) and ARIMA Trend Forecasting

3.1.7. ARIMAX Model on Shampoo

Based on Table 5, which shows the results of testing several ARIMAX models, all models have p-values of 0.000, indicating that the parameters in each model are statistically significant and suitable for use. Therefore, the selection of the best model is primarily based on goodness-of-fit criteria, particularly the AIC value. In ARIMAX modeling, the best model is the one with the smallest AIC value, as it indicates the best balance between model complexity and data-explanatory power. Based on the AIC values in the table, the ARIMAX(3,0,1) model has the lowest AIC value, -88.6302. Thus, ARIMAX(3,0,1) is selected as the best model because it provides an optimal balance in accuracy and has the best performance in explaining historical data patterns.

Table 5. ARIMAX Model Selection Table

ARIMA Model	Log Likelihood	p-value	AIC
ARIMA (1,0,1)	48.86357	0.000	-87.72715
ARIMA (2,0,1)	49.54407	0.000	-87.08815
ARIMA (2,0,2)	49.56096	0.000	-85.12193
ARIMA (3,0,1)	51.31510	0.000	-88.63020
ARIMA (3,0,2)	49.98426	0.000	-83.96851
ARIMA (3,0,3)	51.74299	0.000	-85.48599

The ARIMAX estimation results on Table 6 show that the lnspent_shampoo variable has a significant and positive effect on ln_sales_shampoo, with a coefficient of 0.382 ($p < 0.001$), indicating that an increase in advertising expenditure is associated with an increase in shampoo sales on a logarithmic scale. The constant is negative (-2.394, $p < 0.001$), indicating the base level of sales when all other variables are at their minimum values. In the autoregressive component, the first lag has the strongest and most significant effect (AR(1) = 1.469, $p < 0.001$), reflecting a very strong dependence between current sales and the previous period. The effects of the second and third lags are also significant but negative (AR(2) = -0.214, $p = 0.005$; AR(3) = -0.258, $p = 0.001$), indicating a correction mechanism for excessive fluctuations in the previous two to three periods. The moving average (MA(1)) component is significant with a large negative coefficient (-0.905, $p < 0.001$), which means that shocks in the previous period have a strong corrective effect on the current value. Overall, the high log-likelihood value and the chi-square of 242.595 with a p-value of 0.000 indicate that the model has excellent ability to explain data variation and that the inclusion of exogenous variables significantly improves the accuracy of this time series model.

Table 6. ARIMAX (3,0,1) Modeling Table

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
Lnspent_shampo	0.3816574	0.0077483	49.26	0.000
Const (μ)	-2.3936080	0.3199977	-7.48	0.000
AR (1)	1.4692050	0.0847413	17.34	0.000
AR (2)	-0.2144348	0.0762431	-2.81	0.005
AR (3)	-0.2575453	0.0797621	-3.23	0.001
MA (1)	-0.9052852	0.0823142	-11.00	0.000
Log Likelihood				51.3151
Chi-square				242,595.2000
p-value				0.0000

The white noise test of the ARIMAX (3,0,1) model residuals produced a statistical value of 42.5194 with a p-value = 0.3631. This indicates that the residuals are white noise, i.e., they do not exhibit autocorrelation.

3.1.8. ARIMAX Forecast

The forecasting results with the ARIMAX model based on Figure 8 show that it can follow historical data movements quite well, with the prediction line moving very close to the actual values during the in-sample period. This indicates that the exogenous variables used help explain sales variations. However, during the forecast period, ARIMAX produces a relatively stable pattern that fluctuates slightly around the middle level, without any significant upward or downward trends. This pattern indicates that the model relies on exogenous variables and ARIMA components to maintain a consistent predictive level. In addition, several prediction points experience occasional sharp declines in April 2026, indicating extreme values in the variables or residuals in the model. Overall, ARIMAX provides more stable forecasts than other models because it considers the influence of external variables.

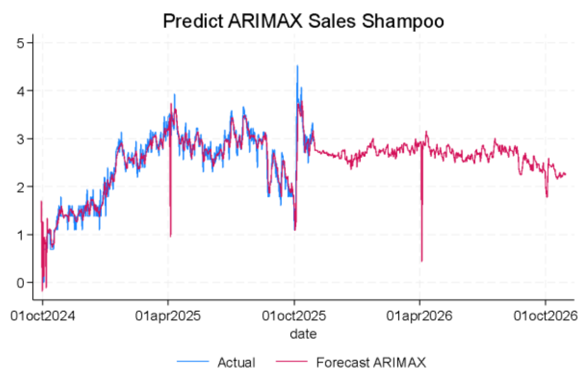

Figure 8. ARIMAX (3,0,1) Forecast Graph

3.1.9. ARIMA, ARIMA Trend, and ARIMAX Forecasting Graph

The comparison graph on Figure 9 shows that the three models, ARIMA (3,0,1), ARIMA with Trend, and ARIMAX (3,0,1), are able to follow historical sales patterns until the end of the in-sample period, with prediction lines moving close to actual data. However, a striking difference appears after entering the forecasting period. The ARIMA model produces projections that tend to decline slowly and then level off, reflecting the nature of a non-seasonal model that returns to its long-term average. In contrast to ARIMA, ARIMA with Trend projects a fairly sharp increase in sales, as it captures the trend component and assumes the upward pattern will continue. Meanwhile, ARIMAX provides more stable predictions with slight fluctuations around a certain level, indicating that the exogenous variables used help the model maintain stability without drastic upward or downward trends. Overall, the results of this graph show that ARIMA provides conservative projections, ARIMA with Trend is optimistic with an upward trend, while ARIMAX provides balance with more stable predictions influenced by external variables included in the model.

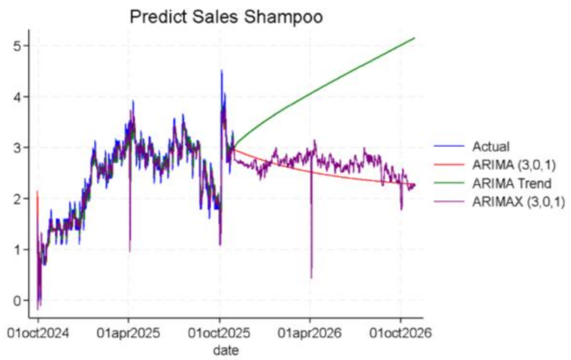

Figure 9. ARIMA, ARIMA Trend, and ARIMAX Forecasting Graphs

3.1.10. MSE, RMSE, MAPE Sales Shampoo

The results of the performance evaluation of the three models on Table 7 show that ARIMAX (3,0,1) has the lowest MSE and RMSE values, with MSE of 88.98 and RMSE of 9.43, indicating that this model provides a slightly lower absolute prediction error. However, in terms of MAPE, the ARIMAX model has a slightly higher value than the ARIMA and ARIMA Trend models. This shows that although ARIMAX reduces the error variance (MSE and RMSE), the model does not achieve a significant improvement in accuracy, as measured by relative average error percentage. Overall, the three models have relatively similar performance, but ARIMA Trend provides the lowest MAPE while ARIMAX excels in MSE and RMSE. From a managerial perspective, these findings indicate that adding advertising expenditure variables to the model helps smooth absolute sales estimates but does not necessarily make predictions much more accurate in percentage terms. In other words, for shampoo products with relatively stable demand patterns, production planning and inventory management decisions can still rely on historical trends without relying entirely on digital advertising fluctuations.

Table 7. MSE, RMSE, MAPE Sales Shampoo Table

Model	MSE	RMSE	MAPE
ARIMA (3,0,1)	89.762080	9.4742852	77.978790
ARIMA Trend	89.740011	9.4731204	77.863468
ARIMAX (3,0,1)	88.979391	9.4328888	78.126944

3.1.11. Monthly Shampoo Sales Forecast

Based on Table 8, although the error patterns for the three models vary, all of them still demonstrate significant deviations from actual values during most parts of the period according to the difference between actual and forecast values. Across the early period (Sept–Dec 2024), ARIMAX offers predictions closest to actuals. e.g. For 1/9/2024 (actual 2.00) ARIMAX had predicted only 0.76 so that is closer than what ARIMA and ARIMA trend did. This indicates that there was something going on in the early stage, when demand is still low but beginning to increase, advertising expenditure contributes to increasing sales. In fact, predictions from ARIMA and ARIMA Trend models are rather stable between early January to April 2025, while for ARIMAX's those on 1/1/25 and against previous day on 1/3/25 start to show slight tendency towards over forecasting.

Table 8. Monthly Shampoo Sales Forecast Data Table

Date	Test Set	ARIMA	ARIMA Trend	ARIMAX
01/09/2024	2,00	13,32	4,07	0,76
01/10/2024	3,00	6,14	4,85	1,70
01/11/2024	4,10	5,90	6,50	3,92
01/12/2024	5,19	6,42	7,63	6,33
01/01/2025	12,39	7,14	9,18	13,51
01/02/2025	13,32	11,00	14,04	14,27
01/03/2025	20,10	12,63	12,40	20,98
01/04/2025	24,13	16,56	20,07	24,30
01/05/2025	17,35	19,78	17,83	18,04
01/06/2025	16,27	17,29	17,43	17,03
01/07/2025	24,26	16,00	19,02	23,94
01/08/2025	16,61	19,68	24,83	18,98
01/09/2025	9,07	16,89	16,28	16,10
01/10/2025	26,43	12,22	21,04	15,89

The managerial implication of this condition is that in rapidly growing demand scenarios, there's indeed a positive correlation between advertising and sales growth, at least up to some point; however, the underlying relationship can be nonlinear and lead to overoptimistic forecasts in the absence of analyzing historical trends as well. In general, ARIMA Trend appears to provide the most consistent performance, with prediction differences that are not too extreme in almost all periods. ARIMA without trend tends to predict lower values, because it lags the upcoming seasonal pattern or emerging trends. In contrast, ARIMAX excels at lower and moderate levels of activity, but occasionally overshoots a given value when realisations rise quickly, particularly in early to mid-2025. Nonetheless, it is observed that ARIMAX continues performing well in some of the peaks and troughs indicating that advertising expenditure variable is still assisting in explaining temporally-reflected variation especially during major market shifts. The downside of this model is as follows: it sometimes forecasts higher levels than actual realizations when demand runs high, hence the management should be cautious not to over-stock itself as a result of over-reliance on promotional effects.

In conclusion, this comparison indicates that shampoo products typically have more stable demand which is less dependent on digital promotions. The correct managerial response is not to pour more money into advertising, but rather to maintain sustained sales trends, build consumer loyalty and use advertising as a tool of evolving demand stability — not as the sole accelerator for any growth.

3.2. Data of Cream

Refer to Figure 10, sales were low at the start of the period, but gradually grew until early 2025, suggesting demand for the product was increasing. Demand kept climbing sharply and reached its maximum around March–April 2025, when sales were at their peak during the period. This large surge indicates a special event, such as a massive promotion, viral marketing, or seasonal momentum carrying heavy consumption. But following this peak, sales halved and have continued to slowly decline. However, the small spikes that occurred in mid to late 2025 were likely due to occasional promotions. By the end of the period, sales fell back to about where they started, suggesting declining market enthusiasm for that product and indicating that the previous high sales were not sustainable.

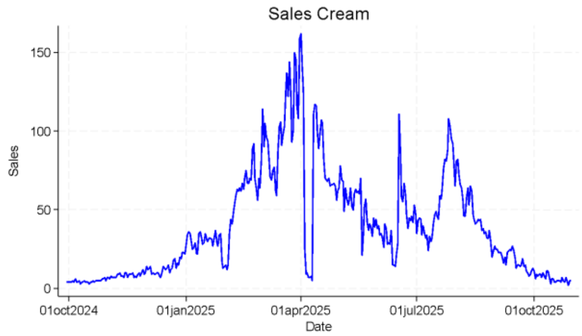

Figure 10. Cream Sales

The line graph on Figure 11 indicates that there are many variations in advertisements spending during this phase (October 2024 - October 2025). On the first date of that period, advertising spending was low and increased slowly until the early start of 2025. This increase then transitioned into a much more intense rising trend with drastic repetitive spikes, peaking around late March to early April 2025, when ad spend reached the most significant level during this period. After this peak phase, ad spend entered a slower downward trend but was still punctuated by multiple large peaks in the mid to late 2025, which likely reflect further marketing or promotion efforts. Towards the end of the observation period, advertising spending returned to low levels, indicating that the intensity of promotions had decreased sharply from the peak period. Overall, this graph pattern indicates a very aggressive advertising strategy focused on specific periods, with high advertising spending in one main phase to drive awareness and demand, followed by follow-up campaigns that were less intense than before.

Figure 11. Cream Advertising Expenditure

3.2.1. Stationarity Testing

Table 9 shows the results of the ADF test of the variables used in the study. Based on Table 1, the sales variable has a p-value < 0.05, indicating that the stationarity level of the variable is at level I(0), so there is no need to differentiate the data.

Table 9. Stationarity Test Table

Variable	Level I(0)	
	Statistic	p-value
Sales Cream	-2.995	0.0354
Ad Spent Cream	-2.713	0.0418

3.2.2. ACF and PACF Cream

The ACF graph on Figure 12 shows the correlation between the ln_sales_cream value and its past values at various lag times. This ACF graph is used to understand the time-series pattern and to help determine the ARIMA time-series model. The ln_sales_cream data shows strong, slowly decreasing autocorrelation, indicating long-term dependence across periods. This pattern is consistent with the AR (autoregressive) process and indicates that sales are greatly influenced by sales in the previous period.

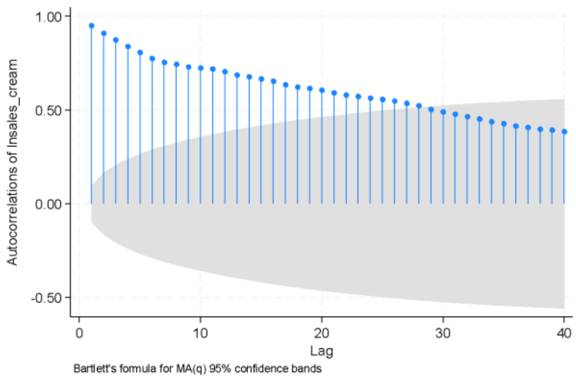

Figure 12. ACF Graph on Cream

The PACF graph on Figure 13 shows the partial relationship between ln_sales_cream and values in previous periods, after controlling for the influence of other lags. This graph identifies the autoregressive (AR) component of the ARIMA model. The graph shows a single large and significant spike at lag 1, while almost all subsequent lags are within the 95% confidence interval and are insignificant. This pattern indicates that the main influence on current sales values comes from the previous period, and the partial relationship at more distant lags is relatively weak and inconsistent. Thus, the data structure tends to follow a low-order AR process.

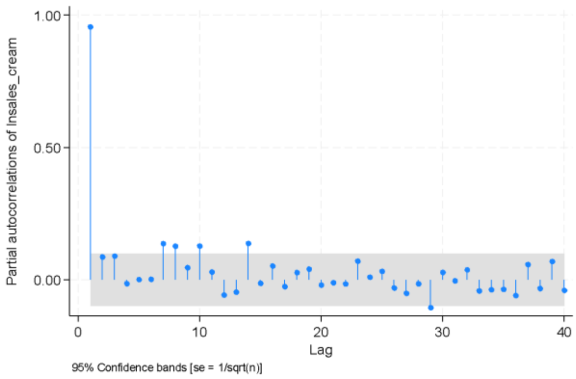

Figure 13. PACF Graph on Cream

3.2.3. Determining the Best ARIMA Model

Table 10 shows the results of testing several ARIMA models, all models have p-values of 0.000, indicating that the parameters in each model are statistically significant and suitable for use. Therefore, the selection of the best model is primarily based on goodness-of-fit criteria, particularly the AIC (Akaike Information Criterion). In ARIMA modeling, the best model is the one with the smallest AIC value, as it shows the best balance between model complexity and data explanatory power. Based on the AIC values in the table, the ARIMA(2,0,1) model has the lowest AIC of 166.144. Thus, ARIMA(2,0,1) is selected as the best model because it provides an optimal balance in accuracy and has the best performance in explaining historical data patterns.

Table 10. ARIMA Model Table

ARIMA Model	Log Likelihood	p-value	AIC
ARIMA (1,0,1)	-82.53630	0.000	173.0726
ARIMA (2,0,1)	-78.07198	0.000	166.1440
ARIMA (1,0,2)	-81.29473	0.000	172.5895
ARIMA (3,0,1)	-81.19746	0.000	174.3949
ARIMA (3,0,2)	-77.92673	0.000	169.8535

3.2.4. Forecasting Model

The ARIMA estimation results on Table 11 show that the ln_sales_cream value is significantly influenced by short-term dynamics, particularly the values in the previous one and two periods. The large and significant AR (1) component (1.751, p < 0.001) indicates that sales in the previous period have a strong influence on the current period. Meanwhile, the negative and significant AR (2) (–0.753, p < 0.001) indicates a short-term correction pattern in the time series. The MA component (1) is also significant and negative (–0.898, p < 0.001), which means that shocks in the previous period have a large corrective effect on current values. Overall, the large and significant chi-square value confirms that the model explains the data movement pattern well.

Table 11. ARIMA (2,0,1) Modeling Table

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
Const (μ)	2.448426	1.1020980	2.22	0.026
AR (1)	1.751256	0.0778694	22.49	0.000
AR (2)	-0.752660	0.0766071	-9.83	0.000
MA (1)	-0.897512	0.0590470	-15.20	0.000
Log Likelihood				-78.07198
Chi-square				457,622.12000
p-value				0.00000

The estimation results on Table 12 show that the trend and constant components are not significant in explaining the variation in lnsales_cream. The trend coefficient has a positive value of 0.0007889 but is not significant (p = 0.889), so there is no evidence of an upward or downward sales pattern over time in the observation period. The constant is also insignificant (p = 0.131), so the average base sales level cannot be statistically determined to be different from zero. Conversely, all time dynamics components, namely AR (1), AR (2), and MA (1), are significant at a high confidence level (p < 0.001). The large and positive AR (1) coefficient (1.7513) indicates that current sales are strongly influenced by sales from the previous period, reflecting strong persistence in the data. AR (2) has a negative coefficient (−0.7528), indicating a corrective or balancing effect from sales two periods prior. Meanwhile, MA (1) has a negative value (−0.8975), indicating that shocks from the previous period have a reducing effect on the current error value. Overall, the model is deemed significant based on a Chi-square value of 419,627.82 (p = 0.000), indicating that the ARIMA structure used can statistically explain the dynamics of cream sales.

Table 12. ARIMA Modeling with Trend Table

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
Const (μ)	2.3019760	1.5225340	1.51	0.131
Trend	0.0007889	0.0056581	0.14	0.889
AR (1)	1.7513110	0.0868764	20.16	0.000
AR (2)	−0.7527584	0.0851962	−8.84	0.000
MA (1)	−0.8975294	0.0690079	−13.01	0.000
Log Likelihood				−78.05229
Chi-square				419,627.82000
p-value				0.00000

3.2.5. White Noise Test

The white noise residual test of the ARIMA (2,0,1) model yielded a p-value of 0.7994 and a test statistic of 32.3616. This indicates that the residuals are white noise, meaning that the residuals do not have an autocorrelation pattern.

3.2.6. Forecasting

The graph on Figure 14 shows a comparison between actual sales values and the results of the ARIMA (2,0,1) forecast model during the out-of-sample period. In general, the ARIMA model is able to follow the historical pattern of the data quite well during the in-sample period, as seen from the prediction line (red), which moves very close to the actual data (blue). This is consistent with previous estimation results, which show that the AR (1), AR (2), and MA (1) components are highly significant, allowing the model to capture the dynamics and persistence of daily sales. Specifically, in the forecast section (after October 2025), it generates a steadily moving easing of this increase. This makes sense since non-seasonal ARIMA tends towards its long-term average when there are either no seasonal patterns or large new shocks. The forecast appears fairly smooth, no sharp peaks are visible anymore and this is the expected behaviour from a stable process, where underlying values tend to be pulled towards steady state. Essentially, the model indicates that following a deep drop-off towards the end of the observation period, sales will slowly return to their equilibrium state. In conclusion, the ARIMA (2,0,1) model is quite capable of recreating past behaviours and giving coherent predictions.

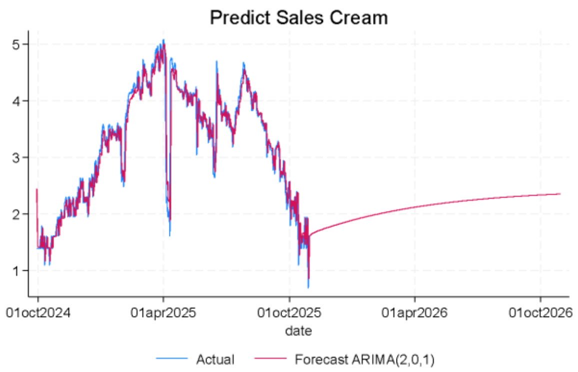

Figure 14. ARIMA (2,0,1) Forecasting

The graph on Figure 15 compares actual data with predicted values from an ARIMA with Trend model for cream sales. Trend model captured the actual data pattern quite smoothly during the in-sample period. The predictive line was very close to the actual line, which means that the model captured the main level of sales movements and trends, although it showed quite sharp fluctuations. The model generates wild predictions with a smooth increasing trend in the out-of-sample period (October 2025 and later). This is consistent with the behavior of the ARIMA with Trend method, which assumes that any change in level and trend from one period to the next will persist into the future. The model also does not include seasonal components, so the predictions are smoother and less volatile than the historical data. Hence the graph indicates an incremental positive sales trajectory into higher levels in the mid-term. In general, since the ARIMA with Trend model describes long-term trends well, and when the analysis emphasizes describing or predicting underlying trends instead of daily changes, this approach might work. These make Predictions from ARIMA with Trend much smoother and less sensitive against short-term fluctuations compared to ARIMA.

Figure 15. ARIMA with Trend Forecasting

The graph on Figure 16 comparing shows the pattern differences between ARIMA (2,0,1) and ARIMA with Trend methods for forecasting cream sales. During the historical period, both models fitted well, with prediction lines closely matching observation values. But when the forecasting period started, the two models produced predictions on opposite sides of a great divide. The ARIMA model produces more moderate projections, with gradual increases around the long-run mean. This captures the fact that ARIMA is carefully capturing short-term autoregressive dynamics. On the other hand, ARIMA Trend shows a much more aggressive growth and trend. ARIMA Trend provides more optimistic predictions because it emphasizes level and trend components, while ignoring autoregressive patterns and short-term fluctuations. Overall, these differences in prediction results show that ARIMA is suitable for forecasting stable patterns influenced by time dependence, while ARIMA with Trend is more appropriate when the analysis objective is to highlight smooth and continuous long-term trends.

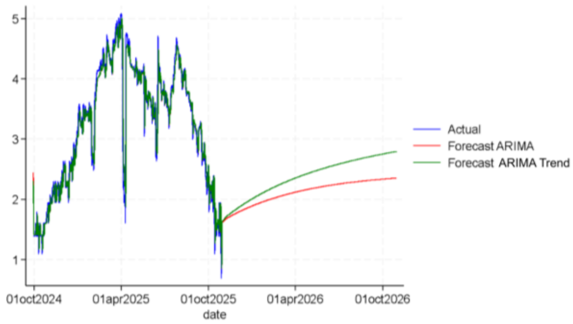

Figure 16. ARIMA (2,0,1) and ARIMA Trend Forecasting

3.2.7. ARIMAX Model on Shampoo

Based on Table 13, which shows the results of testing several ARIMAX models, all models have p-values of 0.000, indicating that the parameters in each model are statistically significant and suitable for use. Therefore, the selection of the best model is more focused on the goodness-of-fit criteria, particularly the AIC value. In ARIMAX modeling, the best model is the one with the smallest AIC value, as it shows the best balance between model complexity and data-explanatory power. Based on the AIC values in the table, the ARIMAX(1,0,1) model has the lowest AIC of -630.6675. Thus, ARIMAX(1,0,1) is selected as the best model because it provides an optimal balance in accuracy and has the best performance in explaining historical data patterns.

Table 13. ARIMAX Model Selection Table

ARIMA Model	Log Likelihood	p-value	AIC
ARIMA (1,0,1)	320.3337	0.000	-630.6675
ARIMA (2,0,1)	321.1647	0.000	-630.3294
ARIMA (2,0,2)	321.8164	0.000	-629.6327
ARIMA (3,0,1)	321.8073	0.000	-629.6146
ARIMA (3,0,2)	321.8658	0.000	-627.7316
ARIMA (3,0,3)	322.0517	0.000	-626.1035

The model estimation results on Table 14 show that the Lnspent_cream variable has a positive and significant effect on the dependent variable, with a coefficient of 0.9378 and a p-value of 0.000, indicating that an increase in spending on cream is strongly associated with an increase in the predicted variable. The model constant is -9.5263 and is significant, indicating that when the independent variable is zero, the dependent variable's baseline is very low. The time dynamics structure in the model also appears significant, with the AR (1) component having a coefficient of 0.9284, indicating a strong relationship with past values, while the MA (1) component has a value of –0.4549, indicating a correction for previous random shocks. All parameters are significant at a high confidence level, given their respective p-values of 0.000. The Log Likelihood value of 320.33 and the Chi-square statistic of 11,398.85 with a p-value of 0.000 indicate that the model has a strong goodness-of-fit and is overall significant in explaining the data variation.

Table 14. ARIMAX (1,0,1) Modeling Table

Parameter	Coefficient	Std. Error	z-Statistic	p-Value
Lnspent_cream	0.9377617	0.0090325	103.82	0.000
Const (μ)	-9.5263050	0.1103691	-86.31	0.000
AR (1)	0.9284380	0.0199625	46.51	0.000
MA (1)	-0.4548757	0.0537047	-8.47	0.000
Log Likelihood				320.3337
Chi-square				11,398.85
p-value				0.000

The white noise residual test of the ARIMAX (1,0,1) model produced a statistical value of 33.7576 with a p-value = 0.7461. This indicates that the residuals are white noise, meaning that the residuals do not have an autocorrelation pattern.

3.2.8. ARIMAX (1,0,1) Forecast

A prediction result pattern from the ARIMAX model forecasting sales of cream products on Figure 17 closely follows actual movements during the observation period. From a visual perspective, the prediction line is almost always in line with the actual data which means that the model captures seasonal dynamics as well as daily changes in sales. In some cases, especially where steep rises or drops are observed, the deviation is more pronounced between actual and forecast, but on an overall scale model still manages to fit to a prominent trend. From early 2026 onwards, forecasted demand demonstrates a steady decrease, suggesting the potential for softer demand. Overall, this graph shows that ARIMAX is a very sound model to predict the cream sales, with minor prediction errors compared to actual trends.

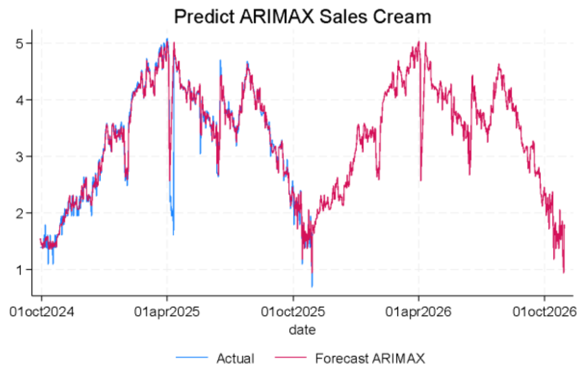

Figure 17. ARIMAX (3,0,1) Forecast Graph

3.2.9. ARIMA, ARIMA Trend, and ARIMAX Forecasting Graph

Graph in Figure 18 compares actual data of Cream Sales with three prediction models: ARIMA (2,0,1), ARIMA Trend, and ARIMAX (1,0,1). Overall, the results of ARIMAX prediction are more similar to the actual data pattern in several ways, especially after the training period. As seen in graph, ARIMAX prediction still closely follows the ups and downs of real data, indicating exogenous variables have positively contributed to improving the model's predictability. On the other hand, ARIMA (2,0,1) presents a conservative projection with a gradual upwards trend, indicating that it reflects internal movement patterns while not modelling external variables. ARIMA Trend Model has produced a more forged and optimistic upward trend compared to the others. Hence, ARIMAX has the best performance when capturing dynamics of cream sales data especially where actual data patterns are strongly governed by time varying external factors.

Figure 18. ARIMA, ARIMA Trend, and ARIMAX Forecasting Graphs

3.2.10. MSE, RMSE, MAPE Sales Cream

The evaluation results on Table 15 show that ARIMAX (1,0,1) performs best among the three models by producing a very low MSE (0.0115), an RMSE of 0.1073, and an MAPE of only 0.64%. This indicates a very low error prediction, means a high level of accuracy from a business perspective. Thus, ARIMAX is able to generate Cream Sales projections that are incredibly close to actual figures. The MSE and RMSE for ARIMA (2,0,1) and ARIMA Trend Models are still much higher with approximately values of 0.089 and 0.298 respectively along with a MAPE value of approximately 1.53%. The ARIMA Trend is marginally better than the basic ARIMA — but not by much. Overall, ARIMAX performs best in terms of both prediction and error stability, making it the most accurate model for predicting the analyzed variable.

Table 15. MSE, RMSE, MAPE Sales Cream Table

Model	MSE	RMSE	MAPE
ARIMA (2,0,1)	0.08894115	0.29823004	1.53238700
ARIMA Trend	0.08827025	0.29710309	1.52588220
ARIMAX (1,0,1)	0.01151118	0.10729019	0.63856446

3.2.11. Monthly Cream Sales Forecast

Table 16. Monthly Cream Sales Forecast Data Table

Date	Test Set	ARIMA	ARIMA Trend	ARIMAX
01/09/2024	4,00	39,26	33,53	3,09
01/10/2024	4,65	14,20	14,07	4,04
01/11/2024	8,47	19,20	18,70	7,48
01/12/2024	13,71	26,78	26,21	12,73
01/01/2025	29,13	34,45	33,95	26,99
01/02/2025	58,11	48,82	48,23	55,71
01/03/2025	102,71	69,80	68,65	94,88
01/04/2025	71,73	95,83	93,32	72,78
01/05/2025	52,39	59,09	56,80	59,59
01/06/2025	41,93	38,99	37,53	47,27
01/07/2025	56,10	29,90	29,61	53,72
01/08/2025	47,39	39,87	40,42	56,34
01/09/2025	17,93	31,20	33,14	14,58
01/10/2025	6,43	10,90	15,21	5,69

Comparing all real values against the predictions for each respective model in the time span of the test, which can be seen on Table 16, it is apparent that ARIMAX has been able to support a statistical analysis that remains true with regards to almost all the period tested. In the early months (September 2024 - December 2024), the predicated values by ARIMA and ARIMA Trend are much larger than actual value, which means a large overestimation. On the contrary, ARIMAX gave out predictions that were closer to actual values and much more realistic. At most times, this pattern continued. Again, at the peak of demand in early 2025, ARIMAX showed considerably better fit on the actual than the other two models which overestimated more than previous predictions. As for the later period of forecast from September to October 2025, ARIMAX performed the best again yielding predictions more closely aligned with those values. Overall, this data reinforces the results of the previous error evaluation that ARIMAX is the most accurate model in capturing data dynamics and producing forecasts that are closest to reality.

4. Conclusion

The results show that product demand at Company X is not solely based on historical sales patterns but is also significantly influenced by the intensity of digital promotions on TikTok. Shampoo products exhibit a relatively more stable demand pattern and have a strong dependence on the previous period (demand persistence). Although TikTok ad spend contributes significantly to increased demand, its impact is not as great as on Cream products. This indicates that Shampoo tends to be a habitual product, so its demand is more stable and not entirely dependent on short-term promotions. In contrast, Cream products show much higher sensitivity to digital advertising spending. The ARIMAX model for Cream products achieves a much better prediction accuracy rate than models without exogenous variables, indicating that Cream demand dynamics are strongly influenced by promotional activities. In other words, Cream is a promotion-driven product with higher demand volatility than Shampoo. From a managerial perspective, these findings have important strategic implications for Company X. A company cannot implement the same marketing strategy to every product segment. Shampoo products are better managed with an approach focused on demand stability, strengthening consumer loyalty, and production planning based on historical trends. In contrast, demand spikes for Cream products are influenced to a large extent by digital advertising campaigns and thus require tighter integration of the marketing & operations segments. The ARIMAX model can be a planning aid for the company to prevent overstocking and understocking risk, particularly products with high sensitivity of promotion. This allows firms to base production and budget allocation decisions on the data accumulated through advertising spend variables, increasing accuracy in forecasting. The findings demonstrate that digital advertising expenditure is not merely a key marketing communication tool but also an operational determinant influencing supply chain and inventory management directly. This study is limited by its reliance on a single exogenous variable (TikTok advertising expenditure), its focus on one company across two product categories, and its use of a classical time-series approach, which may constrain generalizability and model flexibility. Future research should incorporate additional demand-shaping variables, expand cross-industry and cross-company comparisons, and evaluate machine learning or hybrid forecasting models to enhance robustness and predictive accuracy in increasingly complex social commerce environments.

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