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Prophet Based Forecasting of Daily Tiktok Affiliate Revenue Using Operational Variables: The Cutetastic Case

Sri Meri Kurniawati [1*], Fikri Fahru Roji [2], Diqy Fakhrun Shiddieq [3]
[1*,2,3] Digital Business Study Program, Faculty of Economics, Universitas Garut, Garut Regency, West Java Province, Indonesia

Email: Nctsrii4@gmail.com [1*], fikri@uniga.ac.id [2], diqy@uniga.ac.id [3]

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Abstract

This study evaluates the ability of the Prophet model to forecast daily TikTok affiliate revenue for the Cutetastic_ account and examines the contribution of operational variables to forecast accuracy. The dataset comprises 120 days of daily performance records from November 1, 2025, to February 28, 2026, including date, total revenue, number of video posts, video views, product clicks, and products sold. Three modeling scenarios were evaluated: univariate Prophet, Prophet with extra regressors, and Prophet with extra regressors combined with log transformation and parameter adjustment. The data were split chronologically into 106 training observations and 14 testing observations, and model performance was evaluated using MAE, RMSE, and MAPE. The results show that the univariate Prophet model produced a MAPE of 53.86%, whereas Prophet with extra regressors reduced the MAPE to 21.55%. The best performance was achieved by Prophet with extra regressors, log transformation, and parameter adjustment, with an MAE of 8,977,172.95, an RMSE of 11,549,223.21, and a MAPE of 19.31%. These findings indicate that historical revenue patterns alone are insufficient to capture the volatility of TikTok affiliate revenue. Operational variables improved forecast accuracy in this case study, particularly when treated as inputs for conditional forecasting or simulation-based forecasting. Therefore, the results from the regressor-based models should not be interpreted as assumption-free forecasts, but as short-term projections that depend on the availability or simulation of operational inputs.

Keywords:
Daily revenue; Extra regressors; Forecasting; Prophet; Social commerce; TikTok affiliate.

1. INTRODUCTION

The rise of social commerce has transformed how consumers discover, evaluate, and purchase products on digital platforms. Within this ecosystem, TikTok occupies a significant position because it integrates entertainment content, social interaction, algorithm-based recommendations, and transactional activities into a single user experience. Previous studies indicate that purchasing decisions in digital contexts are not determined solely by price and product availability, but also by social interaction, trust, content quality, platform features, and user participation mechanisms (Huang, 2025; Liashenko & Yakymchuk, 2023; Nugroho et al., 2024). At the operational level, creator monetization on TikTok has become increasingly associated with affiliate marketing. Through this mechanism, creators generate revenue from content performance and product transactions that occur through affiliate links. Creator revenue is not only related to content quality, but also to posting intensity, video reach, product clicks, products sold, commissions, and algorithmic momentum. Studies on live streaming and social commerce show that trust, engagement, utilitarian value, hedonic value, interactivity, and social presence contribute to consumer responses in digital purchasing contexts (Hidayat et al., 2025; Huang, 2025; Nugroho et al., 2024). In influencer and affiliate contexts, source credibility, message value, promotional language, and incentive structures are also associated with engagement and campaign performance (Atamimi et al., 2025; Hidayat et al., 2025; Nugroho et al., 2024). Although social commerce research continues to develop, most previous studies have focused on the consumer side rather than on forecasting daily revenue from the creator's perspective. Studies on consumer purchase intention include (Huang, 2022; Liashenko & Yakymchuk, 2023; Nugroho et al., 2024), while studies on consumer trust and engagement include (Asiri et al., 2025; Hidayat et al., 2025; Huang, 2022). Research on social commerce adoption or continuance intention is also represented by (Asiri et al., 2025). Thus, the dominant unit of analysis in the literature is the consumer or platform user, whereas affiliate creators as daily revenue-generating actors remain relatively underrepresented in quantitative modeling, particularly in revenue forecasting. Consumer-oriented research generally explains the psychological or social factors that influence purchase intention, trust, and adoption. By contrast, creators require predictive tools to formulate posting strategies, select products, manage revenue targets, and evaluate the impact of daily activities on revenue. In the Indonesian context, social commerce research has also focused more on factors that drive purchases in live-streaming contexts than on directly modeling creator revenue (Luo et al., 2023; Mandasari et al., 2024; Suhud et al., 2025).

In forecasting studies, Prophet is widely used because it can flexibly model trends, seasonality, and changepoints in business data that are not always stable (Liu et al., 2024; Mazurek et al., 2024). The model applies an additive approach that represents a time series as a combination of trend, seasonal, calendar, and error components. Various applied studies have used Prophet for demand forecasting and sales forecasting, with results showing competitive performance, particularly when the model is combined with hybrid approaches, external variables, or parameter adjustment (Albanna & Diana, 2025; Liashenko & Yakymchuk, 2023; Liu et al., 2024). However, most previous studies have focused on retail, manufacturing, sales, prices, and other business indicators. Research that examines creator revenue within the social commerce ecosystem remains limited. In forecasting literature, model performance is influenced by several factors, including data quality, forecast horizon, validation method, and the suitability of features to the characteristics of the problem being analyzed (Ghazal et al., 2025; Hidayat et al., 2025; Soltaninejad et al., 2024). In forecasting practice, model usefulness is not only related to accuracy, but also to its ability to support decision-making. For TikTok affiliates, daily revenue is influenced by content rhythm, promoted products, audience response, and platform algorithm dynamics. These characteristics suggest that operational information can complement historical revenue patterns in the forecasting process (Nugraha et al., 2024; Nugroho et al., 2024).

The use of additional variables in Prophet models across previous studies is generally dominated by external factors, such as calendars, holidays, specific events, macroeconomic indicators, and historical sales data. In the TikTok affiliate context, daily revenue variation is related to the creator's ongoing operational activities. Variables such as the number of video posts, video views, product clicks, and products sold describe a sequence of processes from content production, audience reach, and product response to sales conversion and revenue generation. These characteristics suggest that operational variables may provide additional information in the forecasting process. Nevertheless, the observed relationships among the variables in this study do not directly represent causal relationships. Based on this discussion, the present study identifies three main gaps. First, there is a domain gap, as studies that specifically model the daily revenue of TikTok affiliate creators remain limited. Second, there is a variable gap, as relatively few forecasting studies use creator operational attributes, such as video posts, video views, product clicks, and products sold, as extra regressors. Third, there is a methodological gap, as limited research has evaluated Prophet configurations sequentially through a univariate model, a model with regressors, and a model with regressors, log transformation, and parameter adjustment using short and volatile affiliate revenue data. Parameter adjustment was performed manually without grid search or systematic optimization methods.

Table 1. Research gap between previous studies and this research

Research	Focus/Method	Object	Evaluation	This Research
Hidayat et al. (2025)	Prophet + regressor + grid search	Restaurant sales	MAPE 3.79%; R^2 0.9787	This study addresses the gap in forecasting daily TikTok affiliate revenue from the creator's perspective by testing Prophet and creator operational variables as extra regressors, with the best result of MAPE 19.31%.
Atamimi et al. (2025)	Default Prophet vs. tuning	Sparse retail data	MAPE 9.50% -> 6.80%	
Huang (2022)	Prophet + macroeconomic regressors	Meta stock	Lowest MAE 14.083	
Huang (2025)	Prophet + exogenous variables	Procurement demand	MAPE 6.7%; R^2 0.947	
Kuang (2024)	Prophet + holiday effects	Alcohol sales	MAPE ±5%	
Liu et al. (2024)	LSTNet-Prophet + PSO	Market demand	MAPE 4.90%-6.86%	

Source: Author's synthesis based on previous studies and research positioning, 2026

Table 1 compares previous studies with the position of the present study. The comparison is based on methodological focus, research object, evaluation results, and the development direction implied by each study. The comparison shows that Prophet has been developed through various approaches, including the addition of external variables, parameter adjustment, and combination with other methods. This study focuses on forecasting creator revenue by positioning creators as economic actors within the social commerce ecosystem. The operational variables represent activities within the social commerce conversion process and are therefore expected to provide a more contextual perspective on daily TikTok affiliate revenue forecasting.

This study contributes to the literature in three ways. First, it extends social commerce research, which has largely been dominated by consumer perspectives, by positioning creators as economic actors who generate daily revenue. Second, it examines the use of creator operational attributes as extra regressors in the Prophet model, so that the modeling process does not rely solely on historical time patterns but also considers content activity and product conversion stages within the social commerce ecosystem. Third, it sequentially evaluates three Prophet model configurations to illustrate the comparison between model simplicity, operational input requirements, parameter adjustment complexity, and the resulting forecast accuracy. The contribution of this study is limited to the case study of the Cutetastic_ account. Therefore, the findings cannot yet be directly generalized to all TikTok affiliate accounts with different characteristics.

2. RESEARCH METHOD

This study employed a quantitative approach with a time-series forecasting design. The unit of analysis was the daily total revenue of the TikTok affiliate account Cutetastic_. The research data consisted of secondary quantitative observational data, as the data were obtained from records of the account's daily performance rather than from experiments involving controlled treatment of the audience. The data source was the daily performance recap of the Cutetastic_ TikTok affiliate account, documented in the Excel file data akun cutetasticc.xlsx on Sheet1. This recap was used as the quantitative data source because it contains daily observations on date, posting activity, revenue, views, clicks, and products sold. The dataset consisted of 120 daily observations covering the period from November 1, 2025, to February 28, 2026. Daily total revenue was positioned as the prediction target, while video posts, video views, product clicks, and products sold were positioned as additional operational features in the second and third models. The use of operational attributes in this study was based on the predictive objective of the modeling process. Therefore, these attributes were used as input information to help the model capture variations in daily revenue, rather than to test causal relationships between variables. During the preprocessing stage, all observations were examined to ensure data quality. The examination showed that there were no missing dates, duplicate dates, or missing values in the attributes used in this study. Since the dataset was limited to one TikTok affiliate account, the methodological scope of this study is case-specific; therefore, the resulting model performance should not be directly generalized to other accounts, product categories, or creator profiles without additional validation.

Table 2. Sample of daily affiliate data used in the study

Obs.	Date	Video Posts	Total Revenue (IDR)	Video Views	Product Clicks	Products Sold
1	2025-11-01	5	37,860,000	1,300,000	115,400	1,800
2	2025-11-02	8	53,630,000	1,390,000	143,100	2,200
...	...	...	...	...	...	...
119	2026-02-27	11	44,820,000	1,240,000	139,600	3,300
120	2026-02-28	10	55,400,000	1,450,000	158,100	3,500

Source: Author's calculation based on the Cutetastic_ daily affiliate dataset, 2026

Table 2 presents the initial and final observations from the raw dataset. The sample shows that each row represents one daily observation with the same operational attributes, namely the number of video posts, total revenue, video views, product clicks, and products sold. Date verification confirmed that the dataset covered a complete 120-day period from November 1, 2025, to February 28, 2026, with 0 missing dates and 0 duplicate dates. Based on this structure, the dataset met the basic requirements for use as a daily time series. The data preprocessing stage included column name standardization, date conversion into time-series format, duplicate date checking, verification of daily observation completeness, numerical format cleaning, and inspection of extreme values. The data were then sorted chronologically to meet the assumptions of time-based evaluation. To maintain consistency with short-term operational scenarios, the last 14 days were treated as testing data, while the remaining earlier observations were used as training data. The selection of a 14-day holdout was aligned with the practical needs of affiliate creators, who generally evaluate content strategies within a weekly to bi-weekly horizon (Avinash et al., 2024; Hossain et al., 2025; Nugroho et al., 2024). The research data structure is shown in Table 3. The table indicates that the data consisted of numerical daily performance attributes, including revenue, number of video posts, video views, product clicks, and products sold. Therefore, this study focused on the model's ability to learn data patterns and forecast revenue, rather than on the analysis of consumer perceptions or behavior, which commonly relies on survey data.

Table 3. Research data structure and operational attributes

Attribute	Data Type	Role in the Model	Operational Description
Date	Date/time	Time index	Sequence of daily observations in time-series format.
Total revenue	Numeric	Prediction target	Daily TikTok affiliate revenue forecasted by the model.
Video posts	Numeric	Operational feature	Number of videos uploaded on a given day.
Video views	Numeric	Operational feature	Number of video views as an indicator of content exposure.
Product clicks	Numeric	Operational feature	Number of product clicks as an indicator of product interest.
Products sold	Numeric	Operational feature	Number of products successfully sold through affiliate activity.

Source: Author's data processing, 2026

The base model used in this study was Prophet. In general, Prophet models a time series through trend, seasonality, special effects, and error components. The basic form of the model is presented in Equation (1).

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t \quad (1)$$

Deep learning approaches have been widely used for multi-horizon forecasting in various forecasting studies. However, these methods are generally applied to datasets with a larger number of observations and involve more complex modeling processes than conventional approaches (Guen & Thome, 2022; Hidayat et al., 2025; Salman et al., 2024). Prophet was selected because it can accommodate extra regressors, offers greater interpretability than more complex approaches, and is suitable for modeling daily business data with a limited number of observations.

This study developed three modeling scenarios. The first scenario used a univariate Prophet model that relied only on daily total revenue as the target variable. The second scenario used Prophet with extra regressors, consisting of video posts, video views, product clicks, and products sold. The third scenario used the same extra regressors, combined with a log transformation of the target variable to stabilize variance and parameter adjustment of the seasonality and changepoint components to improve the model's ability to capture data volatility.

Model evaluation was conducted using three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE was used to measure the average absolute deviation between predicted and actual values. RMSE assigns a larger penalty to extreme errors, making it relevant for revenue data that contain spikes. MAPE was used to measure relative error in percentage form, allowing the comparison between models to be interpreted more easily from a managerial perspective. The evaluation formulas are shown in Equations (2), (3), and (4).

For models with regressors, the holdout evaluation used the actual values of operational attributes during the testing horizon. The use of operational attribute values in the testing period produces forecast accuracy that depends on the availability or simulation of future operational information. These characteristic positions the second and third scenarios as approaches that can be used for short-term operational simulation, rather than as forecasts based solely on historical patterns.

In Equation (1), g(t) represents the trend, s(t) represents the seasonal component, h(t) represents special effects such as holidays or regressors, and εt represents random error (Taylor & Letham, 2018).

$$MAE = (1/n)\ \Sigma\ |yt - \hat{y}t| \quad (2)$$

$$RMSE = \sqrt{[(1/n)\ \Sigma\ (yt - \hat{y}t)^2]} \quad (3)$$

$$MAPE = (100/n)\ \Sigma\ |(yt - \hat{y}t) / yt| \quad (4)$$

Table 4. Modeling scenarios

Scenario	Model Configuration	Input	Evaluation Objective
1	Univariate Prophet	Historical date and total revenue	To measure the ability of historical time patterns to forecast revenue.
2	Prophet + extra regressors	Historical revenue, video posts, video views, product clicks, products sold	To assess the contribution of operational attributes to improved forecast accuracy.
3	Prophet + extra regressors + log transformation + parameter adjustment	Inputs from the second scenario with a log-transformed target and adjusted parameters	To assess whether variance stabilization and parameter adjustment improve model performance.

Source: Author's modeling design, 2026

Table 4 presents the three modeling scenarios used in this study to evaluate the performance of Prophet in forecasting daily TikTok affiliate revenue. Each scenario was designed to represent a different level of model complexity and to examine the additional contribution of operational variables and advanced modeling techniques to forecast accuracy. The first scenario was univariate Prophet, which used only daily total revenue as the target without additional features. This scenario was used to assess the extent to which historical revenue patterns, trends, and seasonality could explain variations in daily revenue.

The second scenario was Prophet with extra regressors. In this scenario, the model incorporated video posts, video views, product clicks, and products sold as operational features. This scenario was designed to examine whether information on the creator's daily activity and social commerce funnel performance could improve forecast accuracy compared with the univariate model.

The third scenario was Prophet with extra regressors combined with log transformation and parameter adjustment. The log transformation was applied to the revenue target to reduce the influence of extreme values and help stabilize variance in volatile data. Conceptually, this transformation was conducted by converting y into log(y) before modeling. After the forecasts were generated on the log scale, the predicted values were converted back to the rupiah scale through inverse transformation or exponentiation so that the evaluation metrics remained interpretable in actual revenue units. Parameter adjustment was performed manually without using grid search or systematic optimization methods.

Table 5. Parameter adjustment information

Component	Description	Status
Model parameters	changepoint_prior_scale = 0.1; seasonality_prior_scale = 5.0; seasonality_mode = multiplicative; weekly_seasonality = True	Used in the model
Determination method	Parameters were determined based on preliminary experiments and data characteristics	Explained
Optimization process	No grid search or systematic optimization was used	Methodological clarification
Modeling data	106 days for training and 14 days for testing	Consistent with the research design

Source: Author's modeling design, 2026

Table 5 provides information on the Prophet parameter configuration used in this study. Parameter adjustment was conducted to control the model's flexibility in capturing trend changes and seasonal patterns in the data.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Data Characteristics and Source

The research data consisted of daily time-series data with a one-day observation interval. The data were obtained from the performance export of the TikTok affiliate account Cutetastic_ through Kalodata and TikTok Analytics. The dataset used in this study was aggregated internal secondary data and did not contain individual consumer identities. The analyzed attributes included the revenue target and daily operational indicators, namely the number of videos posted, video views, product clicks, and products sold.

The data characteristics reflect the unstable nature of social commerce revenue. Daily revenue does not always follow a smooth trend, but may increase sharply when content gains high exposure, when the promoted products are relevant, or when campaign momentum occurs. Conversely, revenue may decline when posting intensity decreases or when the funnel from views to clicks and conversions weakens. This condition explains why modeling based solely on time patterns may be insufficient to capture the dynamics of creator revenue.

Table 6. Descriptive statistics of the daily affiliate dataset

Attribute	Minimum	Mean	Median	Maximum	Total
Video posts	1	13.86	14.50	27	1,663
Total revenue (IDR)	20,700,000	53,148,333.33	54,240,000	130,590,000	6,377,800,000
Video revenue (IDR)	19,510,000	51,981,000.00	53,390,000	130,160,000	6,237,720,000
Showcase revenue (IDR)	0	928,267.58	707,530	3,410,000	111,392,110
Average selling price (IDR)	20,390	31,890.50	34,300	42,170	-
Video views	708,480	1,492,138.92	1,380,000	3,160,000	179,056,670
New followers	25	135.58	120	363	16,270
Product clicks	85,600	144,640.83	138,050	320,100	17,356,900
Products sold	1,400	2,497.50	2,350	9,400	299,700

Source: Author's calculation based on the Cutetastic_ daily affiliate dataset, 2026

Based on Table 6, the average daily total revenue reached IDR 53,148,333.33, with a minimum value of IDR 20,700,000 and a maximum value of IDR 130,590,000. The average posting activity was 13.86 videos per day, while the average number of video views reached 1,492,138.92 views per day. The wide range between the minimum and maximum revenue values indicates substantial volatility. Therefore, univariate modeling may fail to capture variations related to content performance and product interaction.

3.1.2. Model Evaluation Results

The evaluation results show clear differences in performance across the model scenarios. In general, the model that relied only on historical revenue produced relatively high errors, whereas the models that incorporated operational attributes produced substantial improvements in accuracy within the context of this case study. A summary of model performance is presented in Table 7.

Table 7. Comparison of model performance

Model	MAE	RMSE	MAPE
Univariate Prophet	23,464,034.55	26,256,486.08	53.86%
Prophet + extra regressors	9,536,757.29	11,814,068.76	21.55%
Prophet + extra regressors + log transformation + parameter adjustment	8,977,172.95	11,549,223.21	19.31%

Source: Author's data processing, 2026

The univariate Prophet model produced an MAE of 23,464,034.55, an RMSE of 26,256,486.08, and a MAPE of 53.86%. These values indicate that historical time patterns alone were not sufficient to explain fluctuations in TikTok affiliate revenue. Technically, the univariate model tends to capture general trends and recurring patterns, but it is less responsive to daily changes influenced by content activity, product performance, and audience dynamics. Given the volatile nature of the data, the univariate model is at risk of underfitting because the available information is derived only from historical revenue.

Figure 1 illustrates the comparison between actual and forecasted revenue in the univariate Prophet model. The forecast line appears smoother and does not fully capture several sharp increases and decreases in the actual values. This suggests that the univariate model can identify the basic time-series pattern, but loses important information derived from the account's daily operational activities. This condition explains why the univariate model produced the highest MAPE among all scenarios.

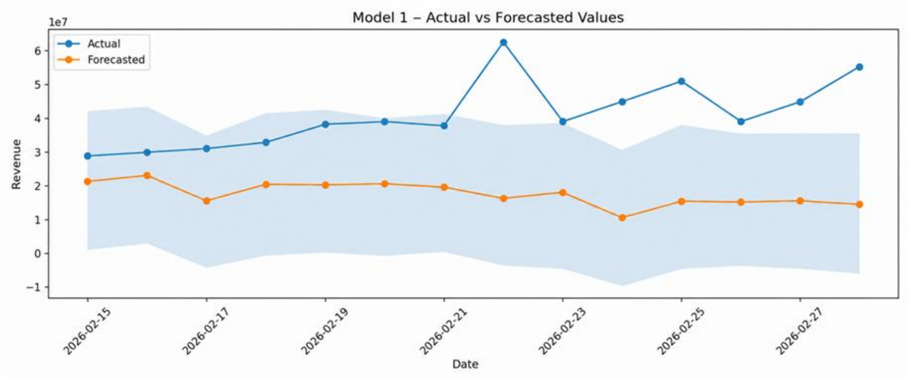

Figure 1. Actual and forecasted daily affiliate revenue using univariate Prophet

When operational attributes were added to the model, performance improved substantially. Prophet with extra regressors reduced the MAE to 9,536,757.29, the RMSE to 11,814,068.76, and the MAPE to 21.55%. This reduction in error indicates that operational information has predictive value for daily revenue variation in the context of this case study. Conceptually, these variables represent the social commerce funnel: video posts represent content production, video views represent audience exposure, product clicks represent product interest, products sold represent conversion, and revenue represents the economic output of the process.

However, the improved accuracy of the model with regressors is related to the characteristics of the variables used. Some regressor variables, particularly product clicks and products sold, are generally observable only after the period has occurred. In addition, products sold has a structural proximity to revenue because affiliate revenue is directly related to transactions. Within this framework, the results of the second model are better interpreted as conditional forecasting, which depends on the availability or simulation of operational inputs, rather than as pure forecasting without assumptions about future information.

Figure 2 illustrates the comparison between actual and forecasted values in the Prophet model with extra regressors. Compared with Figure 1, the gap between the actual and forecasted values appears smaller at several observation points. The forecasts become more responsive because the model receives additional information from content activity and product funnel performance. Nevertheless, the model still shows deviations on certain days because affiliate revenue can also be influenced by factors outside the dataset, such as brand promotions, commission variation, viral momentum, changes in the TikTok algorithm, and the creative quality of content.

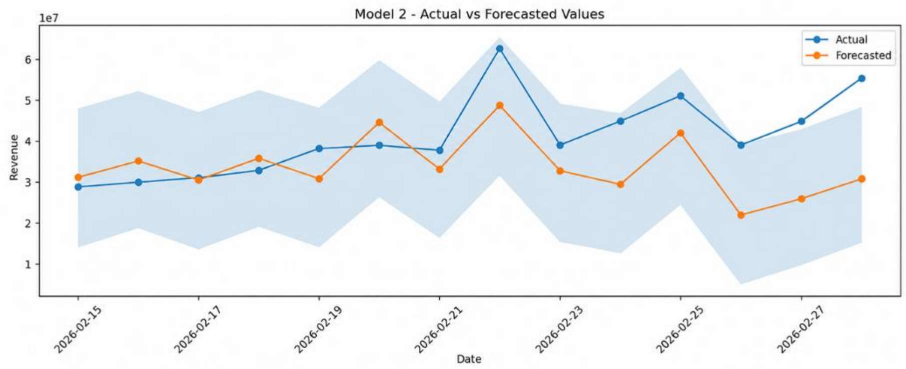

Figure 2. Actual and forecasted daily affiliate revenue using Prophet with extra regressors

The best performance was achieved by the Prophet model with extra regressors, log transformation, and parameter adjustment. This model produced an MAE of 8,977,172.95, an RMSE of 11,549,223.21, and a MAPE of 19.31%. Compared with the second model, the reduction in error was relatively smaller than the improvement obtained from the first model to the second model. This condition indicates that the improvement in accuracy was mainly driven by the integration of operational attributes, while log transformation and parameter adjustment contributed to improving model stability and consistency.

Log transformation helped reduce the influence of extreme revenue values, so that the model was not overly sensitive to very high fluctuations. Parameter adjustment, on the other hand, provided more suitable flexibility in representing changes in trend and seasonal patterns. However, with a limited dataset of 120 observations, the use of a more complex configuration is also associated with a potential risk of overfitting. In this context, the best model performance in this study reflects the configuration most suitable for the data characteristics and evaluation horizon used. Therefore, its interpretation remains contextual and cannot be directly generalized to all TikTok affiliate accounts.

Figure 3 shows the forecast results for the Prophet scenario with extra regressors, log transformation, and parameter adjustment. Visually, the forecast results appear more stable than those of the univariate model and, at several points, show closer alignment with the actual values than the two previous scenarios. This finding is consistent with the numerical evaluation results in Table 7, where this model produced a MAPE of 19.31%, the lowest error rate among the evaluated scenarios. Thus, the third model represents the most suitable approach in this case study for operational and conditional short-term revenue projection.

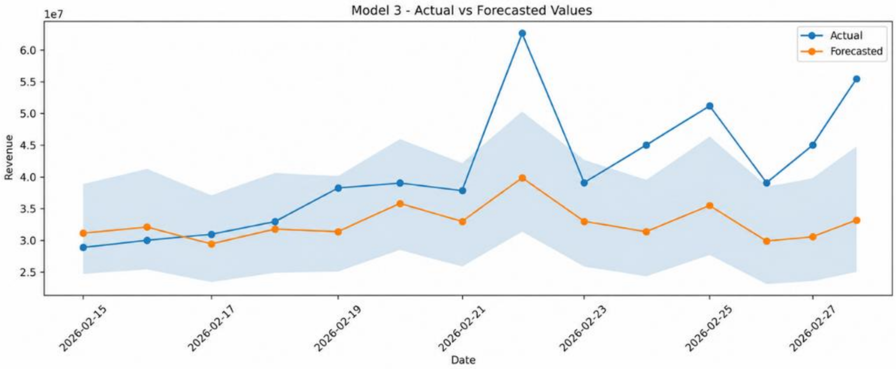

Figure 3. Actual and forecasted daily affiliate revenue using Prophet with extra regressors, log transformation, and parameter adjustment

3.2. Discussion

Academically, the results of this study indicate that creator monetization in the social commerce context has activity-driven characteristics. Creator revenue cannot be projected solely from historical patterns, but is also related to operational indicators that represent the intensity of content production and the effectiveness of the product conversion process. This finding provides an additional perspective to social commerce research, which has largely focused on consumer behavioral aspects, such as purchase intention, trust, engagement, and continuance intention (Budianto et al., 2025; Hajli & Sims, 2015; Lăzăroiu et al., 2020; Wang & Huang, 2022; Yasser & Gayatri, 2023). In this context, the present study focuses on forecasting creator revenue by positioning creators as economic actors within the social commerce ecosystem. Unlike live commerce studies that generally emphasize consumer perceptions of utilitarian value, hedonic value, interactivity, and trust, this study uses operational indicators as predictive features. Several studies have examined purchasing mechanisms in social commerce from the consumer perspective, including factors related to trust, interactivity, utilitarian value, hedonic value, and purchasing decisions (Alrawad et al., 2025; Pranata et al., 2024; Shirazi et al., 2022). In this context, the present study offers a complementary perspective from the managerial viewpoint of creators, specifically through the use of daily activity data as a basis for estimating short-term revenue.

From a forecasting perspective, the findings indicate that feature selection and validation structure play important roles in determining model usefulness. The decrease in MAPE from 53.86% to 21.55% after the addition of regressors reflects the relationship between operational attributes and improved forecast accuracy compared with the use of historical revenue alone. The further decrease to 19.31% after applying log transformation and parameter adjustment indicates a contribution to model stabilization, although the improvement was relatively limited compared with the effect of adding regressors. This pattern highlights that forecasting model development should not focus only on increasing model complexity, but should also consider the balance between accuracy, interpretability, data requirements, and ease of implementation (Makridakis et al., 2020; Petropoulos et al., 2022; Fildes et al., 2022).

The univariate Prophet model offers greater simplicity, is easier to replicate, and does not require assumptions about the availability of future operational features. However, this approach tends to be less responsive in representing volatile revenue fluctuations. Prophet with extra regressors showed better accuracy because it accounted for operational activity, although its application depends on the availability or simulation of inputs for the forecast horizon. Meanwhile, Prophet with extra regressors, log transformation, and parameter adjustment produced the lowest error rate, but also involved higher processing complexity and a potential risk of overfitting, particularly when the dataset is limited and parameter adjustment is not performed through a controlled optimization procedure.

The findings can also be interpreted within the social commerce process flow. Video posting activity is related to content production capacity, while video views represent content exposure and distribution. Product clicks reflect audience interest, products sold indicate the conversion process, and revenue represents the final outcome of this sequence. Integrating these indicators into the Prophet model provides additional information beyond historical time-series patterns. Nevertheless, the relationship among these indicators does not directly represent a causal relationship because other factors may also influence revenue, including brand promotions, price changes, commission structures, content quality, algorithm dynamics, and viral momentum.

From a managerial perspective, the MAPE of 19.31% achieved by the best-performing model indicates its potential use for short-term planning, such as setting daily targets, evaluating posting rhythm, simulating revenue ranges within a two-week horizon, and making decisions related to content intensity. However, this level of accuracy still has limitations for financial decisions that require high precision, such as strict cash planning or medium-term expenditure commitments. In this context, Prophet with extra regressors is more appropriately positioned as a tool to support operational decision-making rather than as a deterministic tool for predicting exact revenue values.

Furthermore, the coefficients or contributions of regressor variables in the Prophet model do not directly reflect causal relationships. The relationships among video posts, video views, product clicks, products sold, and revenue may be influenced by various factors, including multicollinearity, campaign effects, brand promotions, changes in featured products, and viral content momentum. Therefore, the findings of this study represent predictive contributions within the context of the case study and are not intended to prove that a specific operational indicator independently determines revenue growth.

The practical implications of these findings suggest that affiliate creators can use the Prophet model not only to obtain forecast values, but also as a simulation tool for decision-making. For example, creators can compare several operational scenarios, such as increasing the number of daily posts, a decline in product clicks, or an increase in products sold due to a particular campaign. Through this approach, forecasting does not stop at statistical results, but becomes part of content planning, target management, and daily performance evaluation.

In terms of scalability, the model has the potential to be developed for more than one account or product category. However, revenue patterns may differ across accounts due to audience characteristics, niche, commission structure, product prices, and personal branding strength. Therefore, the model configuration that is suitable for the Cutetastic_ account may not produce the same results for other accounts without retraining and further validation. A more realistic approach is to develop a forecasting pipeline that is updated periodically, so that the model remains adaptive to changes in data patterns.

This study has several limitations. First, the data were obtained from a single TikTok affiliate account, which limits the generalizability of the findings to other creators, product categories, or platforms. Second, the observation period covered 120 days, meaning that the model may not fully capture long-term seasonal patterns or sustained changes in audience behavior. Third, several external factors, such as changes in the platform algorithm, brand promotions, discounts, specific periods such as payday, and the creative quality of content, were not included in the model, although these factors may influence the stability of daily revenue.

In addition, the use of regressor variables depends on the availability or simulation of operational inputs within the forecast horizon. When product clicks and products sold are not yet available, a scenario-based approach becomes more relevant than the use of retrospective actual values. At the same time, the products sold variable has a structural proximity to revenue because affiliate revenue is directly linked to transactions. This condition may improve model accuracy, but it also requires careful interpretation to avoid excessive causal claims.

Considering these limitations, the results of the models with extra regressors should be interpreted as conditional simulation tools and decision-support instruments. Meanwhile, the univariate model remains relevant when only historical revenue data are available. In operational practice, model selection can be adjusted to specific needs by considering the balance between accuracy, data availability, ease of interpretation, and the potential risk of overfitting.

4. CONCLUSION

This study evaluated the performance of the Prophet model in forecasting daily TikTok affiliate revenue for the Cutetastic_ account and assessed the contribution of operational variables to forecast accuracy. Three model scenarios were examined: univariate Prophet, Prophet with extra regressors, and Prophet with extra regressors combined with log transformation and parameter adjustment. The analysis used 120 daily observations divided into 106 training observations and 14 testing observations.

The results indicate that the univariate model produced the highest error rate, with a MAPE of 53.86%, whereas the addition of extra regressors substantially reduced the error, with a MAPE of 21.55%. The best performance was achieved by the model with extra regressors, log transformation, and parameter adjustment, which produced a MAPE of 19.31%. These findings indicate that operational attributes, including video posts, video views, product clicks, and products sold, were associated with improved forecast accuracy, while log transformation and parameter adjustment contributed to model stability.

From a practical perspective, the Prophet model can support short-term revenue planning and operational decision simulation, particularly when realistic assumptions about input variables are available. However, the results of the regressor-based models depend on the availability or simulation of operational variables. Therefore, these models are more appropriately interpreted as a conditional forecasting approach rather than as assumption-free forecasts.

This study has several limitations, including the use of a single account, a relatively short observation period of 120 days, and the exclusion of external factors such as campaigns, prices, commission changes, and platform algorithm dynamics. In addition, the structural proximity between products sold and revenue requires careful interpretation. Therefore, the findings should not be generalized to all TikTok affiliate accounts without further validation across different accounts, product categories, creator profiles, and observation periods. Future research is recommended to develop the Prophet-based framework using rollingorigin validation, incorporate event- or campaign-based variables, and test the model across multiple accounts or product categories. A scenario-based approach for future regressor values should also be developed to make the model more applicable for decision support.

REFERENCES

Albanna, H. T., & Diana, D. (2025). Forecasting Penjualan Sembako berbasis Model Prophet: Strategi Efisiensi Stok pada pada Ritel Tradisional. EDUMATIC Jurnal Pendidikan Informatika, 9(3), 698–707. https://doi.org/10.29408/edumatic.v9i3.32251

Alrawad, M., Laradi, S., Lutfi, A., Almaiah, M. A., & Alsharif, A. H. (2025). Investigating the factors influencing social commerce purchase intention: A hybrid study based on PLS-SEM and fsQCA. International Journal of Data and Network Science, 9(4), 1031–1050. https://doi.org/10.5267/j.ijdns.2024.9.016

Asiri, A. Y., Ghani, N. A., & Hamid, S. (2025). Examining the Predictors of Consumer Trust and Social Commerce Engagement: A Systematic Literature Review. Journal of Theoretical and Applied Electronic Commerce Research, 20(3), 247–247. https://doi.org/10.3390/jtaer20030247

Atamimi, F. M. H., Wintanti, W., & Abdillah, G. (2025). Enhanching Prophet Time Series Forecasting on Sparse Data via Hyperparameter Optimizattion: A Case Study in Retail. SinkrOn, 9(2), 1000–1007. https://doi.org/10.33395/sinkron.v9i2.14804

Avinash, A., Widjaja, A., & Karnalim, O. (2024). Analisis Perbandingan Algoritma Machine Learning untuk Forecasting Persediaan Produk Barang Pokok. Jurnal Teknik Informatika Dan Sistem Informasi, 10(2). https://doi.org/10.28932/jutisi.v10i2.9357

Budianto, P. A., Halim, E., Setiawan, A. N. A., & Effendi, H. R. (2025). Exploring the Impact of Evolving Consumer Behavior on Purchase Intention in Social Commerce Environments. Journal of Multimedia Trend and Technology., 4(2), 52–61. https://doi.org/10.35671/jmtt.v4i2.81

Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. International Journal of Forecasting, 38(4), 1283–1318. https://doi.org/10.1016/j.ijforecast.2019.06.004

Ghazal, T. M., Kadhi, N. E., & Ahmad, M. (2025). Unlocking business insights with big data analytics and predictive AI: Discovering hidden patterns for accurate sales forecasting. International Journal of Advanced and Applied Sciences, 12(8), 237–245. https://doi.org/10.21833/ijaas.2025.08.022

Guen, V. L., & Thome, N. (2022). Deep Time Series Forecasting with Shape and Temporal Criteria. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(1), 342–355. https://doi.org/10.1109/tpami.2022.3152862

Hajli, N., & Sims, J. (2015). Social commerce: The transfer of power from sellers to buyers. Technological Forecasting and Social Change, 94, 350–358. https://doi.org/10.1016/j.techfore.2015.01.012

Hidayat, K., Witanti, W., & Ramadhan, E. (2025). Analisis Tren dan Prediksi Penjualan Restoran Menggunakan Model Time Series Prophet. https://doi.org/10.47002/metik.v9i2.1101

Hossain, M. L., Shams, S. M. N., & Ullah, S. (2025). Time-series and deep learning approaches for renewable energy forecasting in Dhaka: a comparative study of ARIMA, SARIMA, and LSTM models. Discover Sustainability, 6(1). https://doi.org/10.1007/s43621-025-01733-5

Huang, Q. (2022). Forecasting Stock Prices Using Multi-Macroeconomic Regressors Based on the Facebook Prophet Model. BCP Business & Management, 25, 231–242. https://doi.org/10.54691/bcpbm.v25i.1762

Huang, S. (2025). Prophet with Exogenous Variables for Procurement Demand Prediction under Market Volatility. Journal of Computer Technology and Applied Mathematics, 2(6), 15–20. https://doi.org/10.70393/6a6374616d.333237

Kuang, Y. (2024). Time series data forecasting: Alcohol sales prediction based on Prophet. Highlights in Science, Engineering and Technology, 85, 597–601. https://doi.org/10.54097/x446dk79

Lăzăroiu, G., Neguriţă, O., Grecu, I., Grecu, G., & Mitran, P. C. (2020). Consumers' Decision-Making Process on Social Commerce Platforms: Online Trust, Perceived Risk, and Purchase Intentions [Review of Consumers' Decision-Making Process on Social Commerce Platforms: Online Trust, Perceived Risk, and Purchase Intentions]. Frontiers in Psychology, 11. Frontiers Media. https://doi.org/10.3389/fpsyg.2020.00890

Liashenko, O., & Yakymchuk, B. (2023). The Application of Time-Series Forecasting Models in Grocery Retail Industry. Theoretical and Applied Issues of Economics, 47, 118–129. https://doi.org/10.17721/tppe.2023.47.11

Liu, B., Li, M., Ji, Z., Li, H., & Luo, J. (2024). Intelligent Productivity Transformation. Journal of Organizational and End User Computing, 36(1), 1–27. https://doi.org/10.4018/joeuc.336284

Luo, X., Lim, W. M., Cheah, J., Lim, X., & Dwivedi, Y. K. (2023). Live Streaming Commerce: A Review and Research Agenda. Journal of Computer Information Systems, 65(3), 376–399. https://doi.org/10.1080/08874417.2023.2290574

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. International Journal of Forecasting, 38(4), 1346–1364. https://doi.org/10.1016/j.ijforecast.2021.11.013

Mandasari, I. C. S., Wardana, I. M., Ekawati, N. W., & Setiawan, P. Y. (2024). The role of live-streaming commerce in moderating the influence of entrepreneurial marketing and e-commerce adoption on the business performance of fashion SMEs. International Journal of Data and Network Science, 8(4), 2097–2106. https://doi.org/10.5267/j.ijdns.2024.6.021

Mazurek, M., Gauda, K., Skrzypek-Ahmed, S., Artiukov, A., & Stalinski, P. (2024). Collection Life Cycle Analysis: Enhancing Market Strategies through Advanced Data Analytics. EUROPEAN RESEARCH STUDIES JOURNAL, 14–24. https://doi.org/10.35808/ersj/3383

Nugraha, A., Pratiwi, M., Ardenis, D. M., Amany, N., Ahmad, S. S., & Sukmawati, A. (2024). Affiliate Marketer a Decent Work for Generation Z in Indonesia? TIJAB (The International Journal of Applied Business), 8(1), 45–55. https://doi.org/10.20473/tijab.v8.i1.2024.51251

Nugroho, A., Patty, M. A., & Karto, A. (2024). Development of Econometric Models for Financial Performance Forecasting in Companies. International Journal of Management Science and Information Technology, 4(2), 381–389. https://doi.org/10.35870/ijmsit.v4i2.3146

Pranata, J. A., Riyanto, M. R. P., Hendrawan, S., & Gunadi, W. (2024). The Effect of Hedonic Motivation and IT Affordance on Impulsive Buying Decision in Social Commerce TikTok. International Journal of Electronic Commerce Studies, 15(2), 62–102. https://doi.org/10.7903/ijecs.2303

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., Bergmeir, C., Bessa, R. J., Bijak, J., Boylan, J. E., Browell, J., Carnevale, C., Castle, J. L., Cirillo, P., Clements, M. P., Cordeiro, C., Cyrino Oliveira, F. L., De Baets, S., Dokumentov, A., ... Ziel, F. (2022). Forecasting: Theory and practice. International Journal of Forecasting, 38(3), 705–871. https://doi.org/10.1016/j.ijforecast.2021.11.001

Salman, D., Direkoğlu, C., Kuşaf, M., & Fahrioğlu, M. (2024). Hybrid deep learning models for time series forecasting of solar power. Neural Computing and Applications, 36(16), 9095–9112. https://doi.org/10.1007/s00521-024-09558-5

Shirazi, F., Hajli, N., Sims, J., & Lemke, F. (2022). The role of social factors in purchase journey in the social commerce era. Technological Forecasting and Social Change, 183, 121861–121861. https://doi.org/10.1016/j.techfore.2022.121861

Soltaninejad, M., Aghazadeh, R., Shaghaghi, S., & Zarei, M. F. E.-. (2024). Using Machine Learning Techniques to Forecast Mehram Company's Sales: A Case Study. Journal of Business and Management Studies, 6(2), 42–53. https://doi.org/10.32996/jbms.2024.6.2.4

Suhud, U., Allan, M., Hoo, W. C., & Juliana, J. (2025). Purchase intention of Muslim consumers on TikTok live stream: Assessing the role of trust, reliability, and TikTok marketing activitie. International Journal of Data and Network Science, 9(4), 981–992. https://doi.org/10.5267/j.ijdns.2024.10.006

Taylor, S. J., & Letham, B. (2018). Forecasting at scale. The American Statistician, 72(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Wang, P., & Huang, Q. (2022). Digital influencers, social power and consumer engagement in social commerce. Internet Research, 33(1), 178–207. https://doi.org/10.1108/intr-08-2020-0467

Yasser, A. S., & Gayatri, G. (2023). The Role of Live Streaming in Building Consumer Trust, Engagement, and Purchase Intention in Indonesian Social Commerce Thrift Clothes Sellers. ASEAN Marketing Journal, 15(2). https://doi.org/10.21002/amj.v15i2.1224