ARIMA, SARIMA, and prophet forecasting for strategic development of non-cash retail payment systems in Indonesia

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Abstract
Indonesia's non-cash retail payment channels exhibit markedly heterogeneous growth patterns, yet forecasting studies in the payment systems domain have rarely compared multiple time series models at the individual channel level or connected forecasting outputs to a management framework capable of informing differentiated strategy. This study addresses both gaps by comparing the forecasting performance of ARIMA, SARIMA, and Prophet across five non-cash retail payment channels in Indonesia using monthly transaction volume data from January 2015 to February 2026, and by classifying the resulting five-year projections according to product life cycle theory. Model accuracy was evaluated using mean absolute error, root mean squared error, and mean absolute percentage error on a holdout test period. The results show that no single model performs best across all channels: ARIMA provides the most accurate projections for two channels, Prophet performs best for two channels, and SARIMA performs best for the remaining channel. Based on projected growth through 2030, three channels are classified as being in a growth stage and two in a maturity stage, each warranting a distinct strategic emphasis. These findings offer a replicable approach for translating channel-level forecasts into differentiated, theoretically grounded payment system development strategy.

***Keywords**: ARIMA, SARIMA, Prophet, forecasting, product life cycle, payment systems*

Introduction
Between 2015 and 2025, non-cash retail payment transactions in Indonesia expanded substantially across nearly all channels: electronic money transaction volume grew from approximately 591 million to over 32 billion transactions annually, while proprietary banking channels rose from 2.78 billion to over 28 billion transactions over the same period (Bank Indonesia, 2026). This expansion reflects both technological advancement and shifting consumer preferences toward more efficient, accessible, and secure means of payment, a pattern also observed globally: the accelerated diffusion of digital and contactless payment solutions during the COVID-19 pandemic reshaped consumer payment behavior across multiple markets (Graziano et al., 2025), while the broader evolution of electronic payment adoption has been shown to depend heavily on network effects and market power within two-sided payment card markets (Li et al., 2020) and on the relative security, sustainability, and convenience trade-offs between digital and physical means of payment (Bartesaghi et al., 2026). Beyond convenience, digital payment adoption has been shown to support financial inclusion and broader economic development by lowering

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transaction costs and improving the accountability of financial flows (Gajjar, 2020), with cross-country evidence linking a one-percentage-point increase in digital payment use to measurable gains in GDP per capita growth and reductions in informal sector employment (Aguilar et al., 2024). Yet this aggregate growth conceals considerable heterogeneity: the five non-cash retail payment channels tracked by Bank Indonesia, namely debit cards, credit cards, electronic money, the national clearing system, and proprietary banking channels, exhibit markedly different growth trajectories, with more conventional channels such as debit cards and the national clearing system growing far more moderately than digitally native channels over the same period. This divergence suggests that the strategic needs of each channel are unlikely to be uniform, which motivates the central premise of this study: that channel-level forecasting, rather than aggregate-level observation, is a more appropriate basis for strategic decision-making in payment system development.

Adoption of specific digital payment instruments in Indonesia has itself been the subject of a growing body of empirical research. At the individual consumer level, ease of use, perceived usefulness, trust, and social influence have consistently been found to shape the adoption of QRIS-based payments (Gunawan et al., 2023) and of digital payment systems more broadly in emerging-economy settings, where financial literacy plays an additional mediating role (Ly & Ly, 2024). At the business level, adoption of cashless payment systems has been linked to technological compatibility, management support, and competitive pressure within a Technology-Organization-Environment framework (Rahman et al., 2022). These studies collectively point to individual- and firm-level behavioral and organizational factors as key drivers of digital payment adoption, complementing the macro-level evidence on aggregate digital payment growth discussed above.

Time series forecasting provides one means of anticipating these divergent trajectories. Autoregressive Integrated Moving Average (ARIMA) and its seasonal extension (SARIMA) remain among the most widely used approaches for modeling time-dependent data, owing to their capacity to capture autocorrelation and, in the seasonal case, recurring periodic patterns (Box et al., 2015). More recently, the Prophet model has gained traction as a decomposable forecasting approach that separates trend, seasonality, and holiday effects, offering greater flexibility in capturing non-linear growth patterns than conventional ARIMA-family models (Taylor & Letham, 2018). A broad review of the forecasting literature across finance, health, weather, and network-traffic domains similarly concludes that neither classical statistical models nor machine learning approaches consistently dominate one another, with relative performance instead depending on the structure of the underlying data (Kontopoulou et al., 2023). Comparative evidence on the relative performance of these models remains mixed and appears highly dependent on the characteristics of the underlying series: Kwarteng and Andreevich (2024) found that Prophet outperformed both ARIMA and SARIMA in forecasting pharmaceutical demand, whereas Abdullah et al. (2026) reported the opposite pattern when forecasting Indonesian banking stock prices, with SARIMA consistently achieving lower MAPE than Prophet across all series examined. A related application to banking time series similarly demonstrates ARIMA's continued relevance for financial forecasting: Al Wadi et al. (2024) found that combining ARIMA with wavelet-based decomposition substantially improved prediction accuracy for a banking sector stock index on the Amman Stock Exchange. A similar advantage for ARIMA-family models has been reported in retail and public health forecasting contexts: Lima et al. (2024) found that ARIMA outperformed both regression-based decomposition and the Holt-Winters method when forecasting retail trade across seven European countries, and Chen and Zhou (2026) found that SARIMA produced more consistent forecasts than Prophet and other alternatives when predicting hospital infection trends. Similar model-dependent findings have been reported directly in financial and commodity forecasting contexts: Angelo et al. (2023) found that Prophet outperformed ARIMA when forecasting Bitcoin prices at daily and weekly intervals, while ARIMA performed better at the monthly interval, and Divisekara et al. (2020) reported that a seasonal SARIMA specification best captured the seasonality and volatility of red lentil commodity prices.

This inconsistency across studies indicates that no single forecasting model can be assumed to perform best across all time series, even within a related domain such as financial or payment transactions; model performance instead appears to depend on the specific statistical characteristics of each series, including trend linearity, seasonal regularity, and structural stability. Despite this, empirical studies on Indonesia's digital payment landscape have more commonly examined the determinants of adoption or its macroeconomic impact at an aggregate or panel level. For instance, Badrawani et al. (2025) examined the influence of digital payments on regional economic growth using a 33-province panel dataset, Naibaho et al. (2023) examined the effect of electronic money on Indonesia's money supply, and Gajjar (2020) analyzed cross-country determinants of digital payment adoption, rather than forecasting channel-level trajectories using multiple comparative time series models.

A further gap concerns the translation of forecasting outputs into strategic recommendations. Most forecasting studies conclude with a discussion of predictive accuracy, without explicitly connecting projected trajectories to a management framework capable of informing differentiated strategic action. This study addresses that gap by drawing on product life cycle (PLC) theory, which posits that a product or service moves through distinct stages, namely growth, maturity, and decline, each of which calls for a different strategic emphasis, ranging from capacity expansion and risk management during growth, to defensive repositioning during maturity, to selective retention or repositioning during decline (Levitt, 1965). This premise is broadly consistent with contingency theory, which holds that organizational effectiveness depends on the fit between an organization's structure or strategy and the specific conditions it faces, rather than on the uniform application of a single best approach (Lawrence & Lorsch, 1967; Amhalhal et al., 2022). Within financial technology specifically, differentiated competitive strategy has been shown to depend on the particular characteristics of each service offering, such as the extent to which it can be differentiated from competitors, further supporting the case against a one-size-fits-all approach to strategy across payment channels (Ng et al., 2023). While PLC theory was originally developed in the context of consumer products, it has since been extended to financial and corporate contexts, where life cycle stage has been shown to shape investment and strategic decision-making patterns (Hoberg & Maksimovic, 2022). Applied at the level of a payment channel rather than a single product, forecast-derived growth trajectories can similarly be used to classify each channel into a corresponding life cycle stage, providing a theoretically grounded basis for differentiating strategic recommendations rather than treating all channels uniformly.

This study addresses these gaps by systematically comparing the forecasting performance of ARIMA, SARIMA, and Prophet across five non-cash retail payment channels in Indonesia, evaluated for transaction volume. Rather than assuming the superiority of any single model, this study identifies the best-performing model for each channel based on Mean Absolute Percentage Error (MAPE), and subsequently classifies each channel according to its projected growth trajectory using a product life cycle lens. In doing so, this study contributes both a methodological comparison relevant to time series forecasting in the payment systems domain and a theoretically grounded, strategy-oriented framework intended to support the formulation of differentiated, channel-specific development strategies.

Methods

This study employs a quantitative, comparative time series design to evaluate and select the most accurate forecasting model for each non-cash retail payment channel in Indonesia, before translating the resulting projections into a product life cycle-based strategic classification. The data used consist of monthly transaction volume for five non-cash retail payment channels, namely debit cards, credit cards, electronic money, the national clearing system, and proprietary banking channels, obtained from Bank Indonesia's Payment System and Financial Market Infrastructure Statistics (SPIP) for the period January 2015 to February 2026. Volume rather than transaction value was selected as the metric of interest because it more directly reflects the frequency and intensity of channel usage, which is the primary concern of this study's forward-looking, channel-level analysis. This produces five distinct time series, one for each channel, each modeled and evaluated independently.

Figure 1 outlines the overall research framework adopted in this study, adapted from the Cross-Industry Standard Process for Data Mining (CRISP-DM). The process proceeds from an initial business understanding stage, in which the strategic problem motivating this study is framed, through data understanding and preparation, comparative model development, accuracy-based model evaluation, and a final deployment stage in which the resulting forecasts are translated into a product life cycle-based strategic classification.

Prior to modeling, the data were cleaned to correct identified inconsistencies, including a temporal misalignment in one series and unit inconsistencies and transcription errors in several others; each series was then split chronologically into a training set and a holdout test set to allow out-of-sample evaluation of forecasting accuracy. Three forecasting models were subsequently developed and compared for each series: ARIMA, its seasonal extension SARIMA, and Prophet, all implemented in Python to ensure methodological consistency across models. Table 1 reports the descriptive statistics of the monthly transaction volume series for each channel over the full sample period (January 2015 to February 2026, 134 monthly observations per channel).

The descriptive statistics in Table 1 reveal considerable heterogeneity in both scale and volatility across channels. Electronic Money records the highest mean monthly volume (960,878 thousand transactions) and, together with the Proprietary channel, the highest relative dispersion, with standard deviations corresponding to coefficients of variation of 0.92 and 0.81 respectively, more than three times that of Debit Card (0.15) or the National Clearing System (0.17). This disparity reflects sustained structural growth over the observation period rather than short-term fluctuation alone, and foreshadows the comparatively higher forecasting error subsequently observed for these two channels. The pronounced difference in scale across channels, ranging from a few thousand transactions per month for the National Clearing System to nearly a million for Electronic Money, further motivates the use of a scale-independent accuracy metric, namely MAPE, as the primary criterion for model selection, as described below.

Business Understanding
Formulate the research problem: heterogeneous growth across five non-cash retail payment channels requires channel-specific, forward-looking strategy.

↓

Data Understanding
Monthly transaction volume for five channels (Debit Card, Credit Card, Electronic Money, National Clearing System, Proprietary); Bank Indonesia SPIP, January 2015–February 2026.

↓

Data Preparation
Data cleaning (temporal misalignment, unit and transcription errors) and chronological train / holdout-test split.

↓

Modelling
ARIMA, SARIMA, and Prophet fitted independently for each of the five channel-level time series.

↓

Evaluation
Forecast accuracy assessed on the holdout test set using MAE, RMSE, and MAPE; best model selected per channel based on the lowest MAPE.

↓

Deployment
Five-year projection (2026–2030) using the best model per channel, used to compute CAGR, classify each channel by product life cycle stage, and derive differentiated strategic recommendations.

Figure 1. Research Framework adapted from CRISP-DM

Table 1. Descriptive Statistics of Monthly Transaction Volume by Channel

Channel	N	Mean	Std. Dev.	Min	Max
Debit Card	134	541,958.50	82,656.19	337,479.00	676,564.00
Credit Card	134	29,535.39	6,661.37	18,602.00	49,195.00
Electronic Money	134	960,877.87	881,497.25	27,056.00	3,158,269.00
National Clearing System	134	12,303.82	2,066.00	8,335.00	18,262.00
Proprietary	134	878,722.94	709,570.33	228,248.49	2,800,919.10

Note: Volume expressed in thousand transactions per month.

The ARIMA model specifies the value of a series at time t as a function of its own past values and past forecast errors, following the general Box-Jenkins formulation:

$$\varphi(B)(1 - B)dYt = \theta(B)\varepsilon t \qquad (1)$$

Where Yt denotes the value of the series at time t; φ(B) and θ(B) are the autoregressive and moving average polynomial operators in the lag operator B; d is the order of differencing; and εt is the error term at time t (Box et al., 2015). For each channel, the order (p, d, q) was selected independently via a grid search over candidate specifications, choosing the combination that minimized the Akaike Information Criterion (AIC) on the training data, an approach shown to materially improve forecast accuracy relative to fixed or default model specifications (Sah et al., 2023). The resulting specifications were ARIMA(3,0,3) for Debit

Card, ARIMA(2,1,2) for Credit Card, ARIMA(3,2,3) for Electronic Money, ARIMA(0,1,1) for the National Clearing System, and ARIMA(1,2,2) for the Proprietary channel, reflecting substantial heterogeneity in the differencing and autoregressive structure required to render each series stationary.

More formally, the seasonal ARIMA (SARIMA) specification augments Equation (1) with a seasonal autoregressive and moving average component of order (P, D, Q) at seasonal period s:

$$\Phi(Bs)\varphi(B)(1 - B)d(1 - Bs)DYt = \Theta(Bs)\theta(B)\varepsilon t \quad (2)$$

Where Φ(Bs) and Θ(Bs) denote the seasonal autoregressive and moving average polynomial operators, D is the order of seasonal differencing, and s is the length of the seasonal cycle, set to 12 for the monthly series analyzed in this study (Box et al., 2015).

As with ARIMA, the seasonal order (P, D, Q) and non-seasonal order (p, d, q) were selected independently for each channel via grid search minimizing AIC on the training data, with the seasonal period fixed at s = 12. The resulting specifications were SARIMA(0,1,1)(1,0,0,12) for Debit Card, SARIMA(0,1,1)(1,0,1,12) for Credit Card, SARIMA(0,1,0)(0,0,1,12) for Electronic Money, SARIMA(0,1,1)(1,0,0,12) for the National Clearing System, and SARIMA(1,2,2)(1,0,0,12) for the Proprietary channel.

Prophet, by contrast, forecasts each series as an additive decomposition of trend, seasonality, and holiday components:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t \quad (3)$$

Where g(t) is a piecewise-linear or logistic trend function capturing non-periodic changes in the series, s(t) represents periodic seasonal effects modeled using a Fourier series, h(t) captures the effect of holidays or other irregular events, and εt is an error term (Taylor & Letham, 2018). This additive, curve-fitting structure allows Prophet to accommodate abrupt trend changes and non-linear growth patterns that classical ARIMA-family models may capture less flexibly.

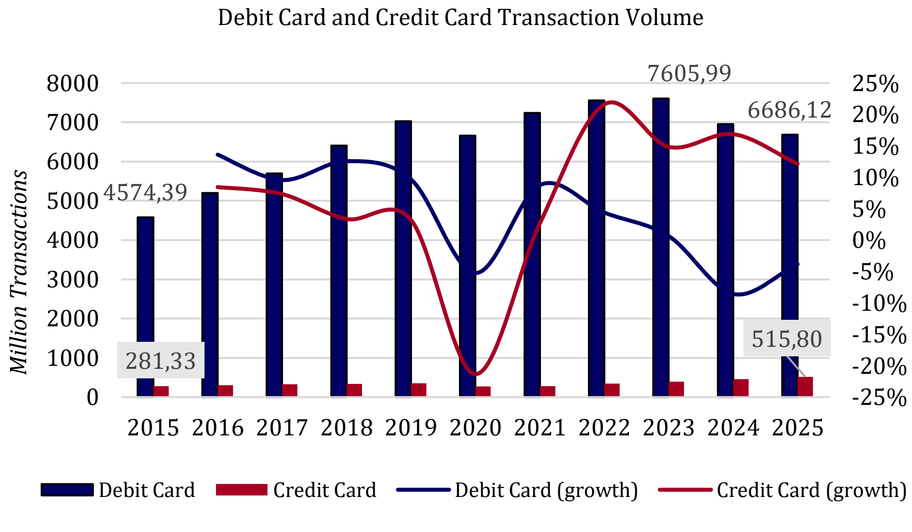
The changepoint prior scale, which governs the flexibility of the trend component in accommodating structural changes, was tuned independently for each channel via grid search, selecting the value that minimized forecasting error on the holdout validation period. The resulting values were 0.80 for Debit Card, 0.30 for Credit Card, 0.30 for Electronic Money, 0.05 for the National Clearing System, and 0.50 for the Proprietary channel. The comparatively low value for the National Clearing System is consistent with its smoother, near-linear historical trajectory (Figure 2b), whereas the higher value for Debit Card accommodates the trend deceleration visible from 2023 onward (Figure 2a).

Forecasting accuracy for each model was evaluated on the test set using three complementary metrics: the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE), and the Mean Absolute Percentage Error (MAPE). MAE and RMSE report error magnitude on the original scale of each series, with RMSE placing proportionally greater weight on larger errors due to its quadratic form, while MAPE expresses error as a scale-independent percentage, allowing accuracy to be compared across channels of markedly different magnitude (Hyndman & Koehler, 2006; Koutsandreas et al., 2022). Because the five series analyzed in this study differ substantially in scale, ranging from channels with several hundred thousand transactions to channels with tens of billions, MAPE was adopted as the primary criterion for selecting the best-performing model for each channel, with MAE and RMSE reported alongside it to provide a fuller picture of forecast error. For each of the five channels, the model with the lowest MAPE was selected as the best-performing model and subsequently used to generate five-year projections for the 2026–2030 period.

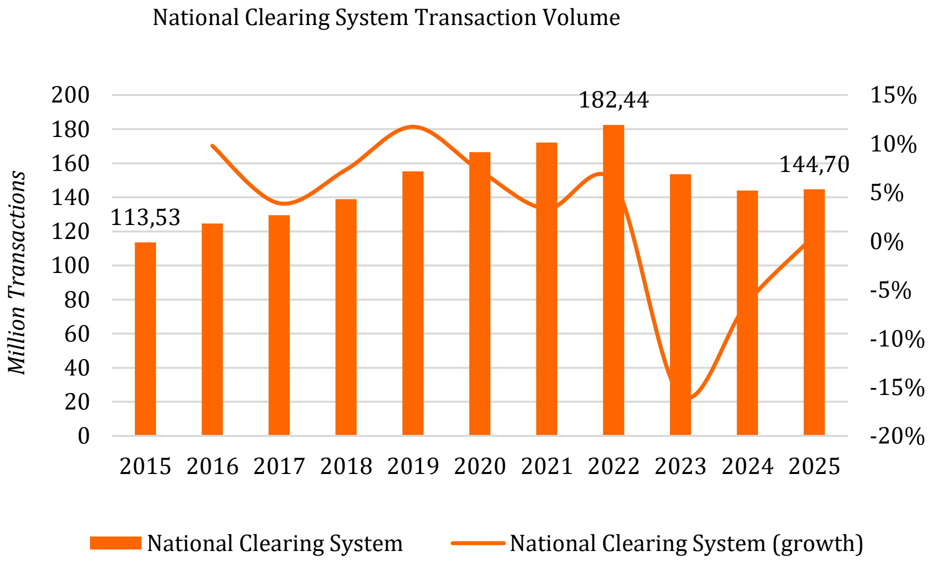
The resulting projections were then used to compute the compound annual growth rate (CAGR) for each channel, which served as the basis for classifying each channel into a corresponding product life cycle stage. Channels with a projected CAGR above 3% were classified as being in a growth stage; those with a CAGR between 0% and 3% were classified as being in a maturity stage, reflecting stabilizing rather than expanding demand; and channels with a negative projected CAGR were classified as being in a decline stage. This classification subsequently forms the basis for the strategy formulation discussed in the following section, in which channels within the same life cycle stage are treated as warranting a similar strategic emphasis, consistent with the differentiated strategic implications associated with each stage under product life cycle theory (Levitt, 1965).

Result and Discussions

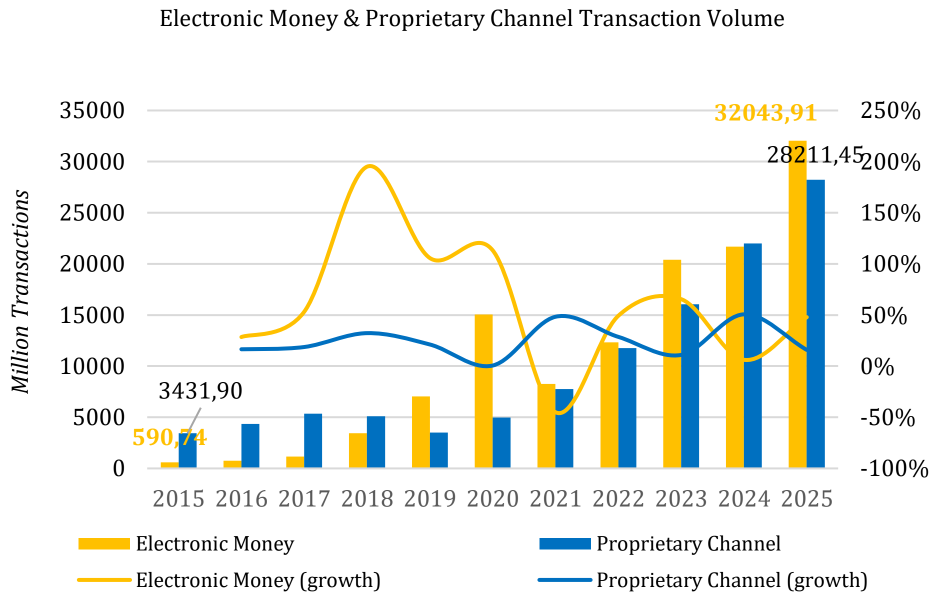
Before comparing formal forecasting accuracy, Figure 2 presents the historical trajectories of monthly transaction volume for each channel over the observation period, providing empirical context for the heterogeneous growth patterns motivating this study. Debit Card and Credit Card, shown in Figure 2(a), exhibit comparatively steady, moderate growth throughout the period, with Debit Card volume roughly stabilizing from 2023 onward. The National Clearing System, shown in Figure 2(b), grew gradually until peaking in 2022 before entering a mild contraction and subsequent plateau. Electronic Money and the Proprietary channel, shown in Figure 2(c), display markedly steeper and more volatile growth, particularly from 2019 onward, consistent with the accelerated adoption of digital payment instruments during and after the COVID-19 pandemic.



(a) Debit and Credit Card



(b) National Clearing System Transaction



(c) Electronic Money & Proprietary Channel

Figure 2. Historical Volume Trends of Non-Cash Retail Payment Channels, 2015–2025: (a) Debit Card and Credit Card; (b) National Clearing System; (c) Electronic Money and Proprietary Channel

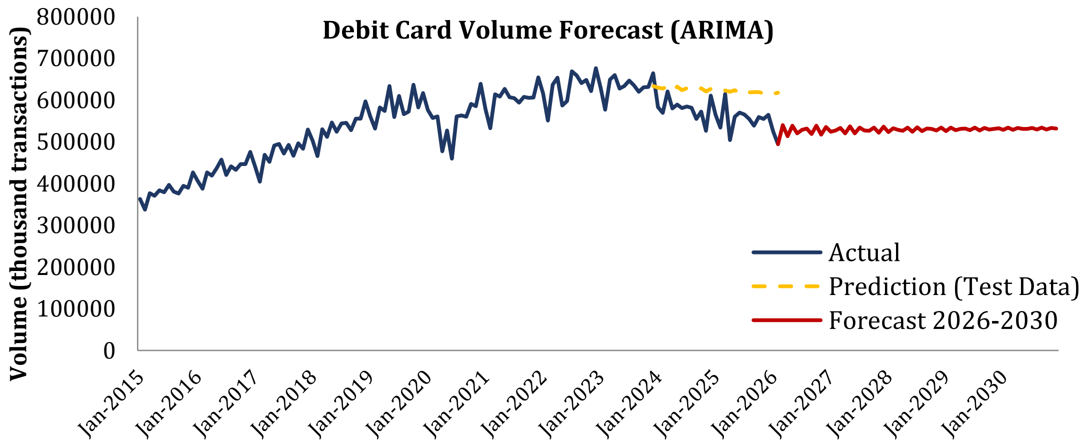
Table 2 presents the forecasting accuracy of ARIMA, SARIMA, and Prophet across the five non-cash retail payment channels, evaluated on the holdout test period (December 2023 to February 2026) using MAPE. Consistent with the mixed findings reported in prior comparative forecasting studies (Abdullah et al., 2026; Kwarteng & Andreevich, 2024), no single model achieves the lowest MAPE across all five channels: ARIMA performs best for two channels (Debit Card and Electronic Money), Prophet performs best for two channels (Credit Card and Proprietary), and SARIMA performs best for the remaining channel (the National Clearing System). The advantage of SARIMA's seasonal component appears channel-specific rather than universal: it improves on ARIMA's MAPE for the National

Clearing System (6.99% versus 8.04%), whose monthly batch-clearing cycle plausibly carries genuine seasonal regularity, but does not do so for the other four channels, where trend behavior rather than seasonality appears to dominate volume fluctuations. The magnitude of the gap between the best- and worst-performing model varies substantially by channel: for Electronic Money, ARIMA's MAPE (14.63%) is less than half of SARIMA's (30.12%), whereas for Credit Card, Prophet's MAPE (2.68%) is roughly a fifth of ARIMA's (14.83%). This pattern is consistent with Angelo et al. (2023), who similarly found that the relative advantage of Prophet over ARIMA in forecasting Bitcoin prices depended heavily on the temporal granularity and volatility characteristics of the series examined, rather than holding uniformly across contexts; a comparable data-dependent pattern was also reported by Namakhwa et al. (2024), who found ARIMA robust in capturing temporal and seasonal patterns in mobile money transaction volumes, further underscoring that model performance in transaction-based time series cannot be generalized from a single prior application.

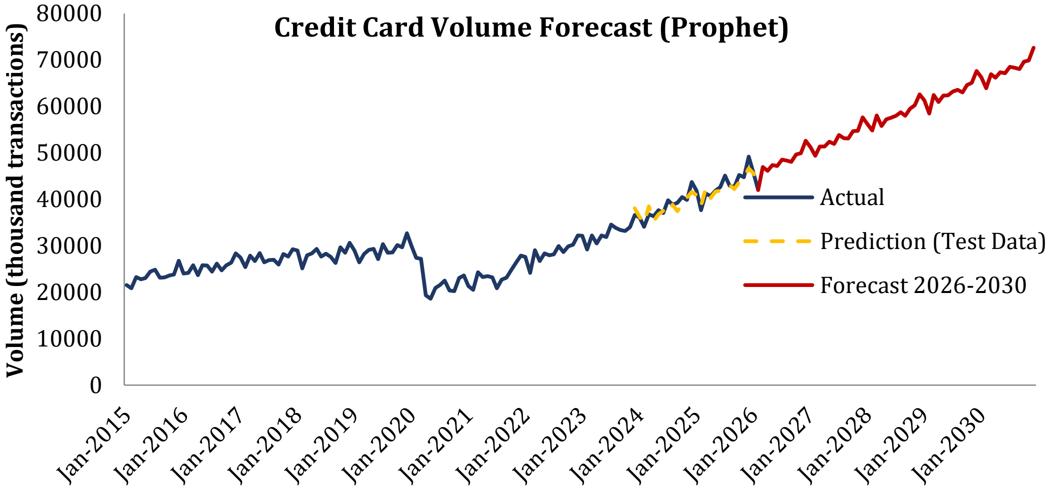
Table 2. Forecasting Accuracy Comparison (MAPE)

Channel	ARIMA (%)	SARIMA (%)	Prophet (%)	Best Model
Debit Card	10.59	11.88	15.66	ARIMA
Credit Card	14.83	11.13	2.68	Prophet
Electronic Money	14.63	30.12	15.31	ARIMA
National Clearing System	8.04	6.99	9.01	SARIMA
Proprietary	11.16	11.22	10.05	Prophet

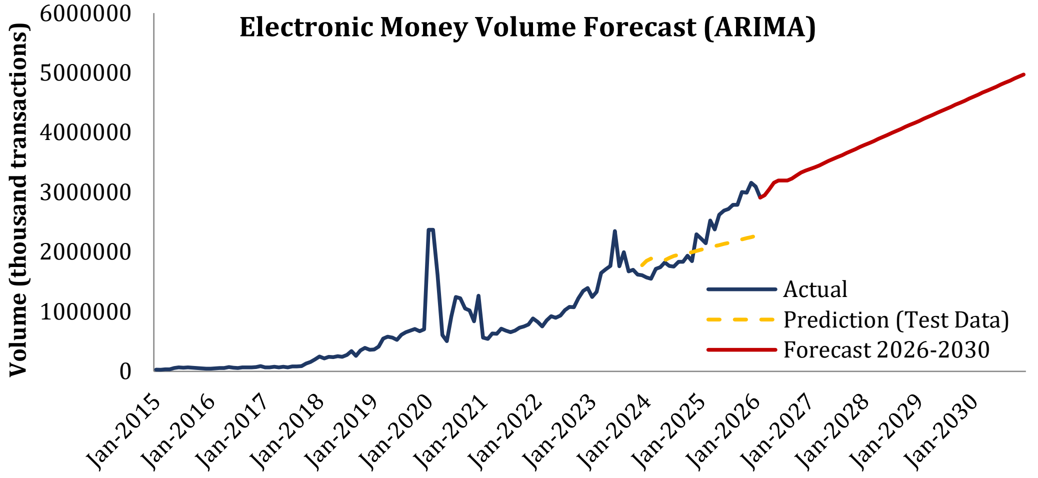
Figure 3 visualizes the resulting five-year projections generated by the best-performing model for each channel. The contrast between channels is pronounced: Debit Card (a) and the National Clearing System (d) both extrapolate close to their most recent stable level, consistent with the comparatively low, near-linear historical growth observed in Figure 2, whereas Credit Card (b), Electronic Money (c), and the Proprietary channel (e) project continued upward trajectories through 2030, reflecting the sustained growth momentum captured by their respective best-fitting models.



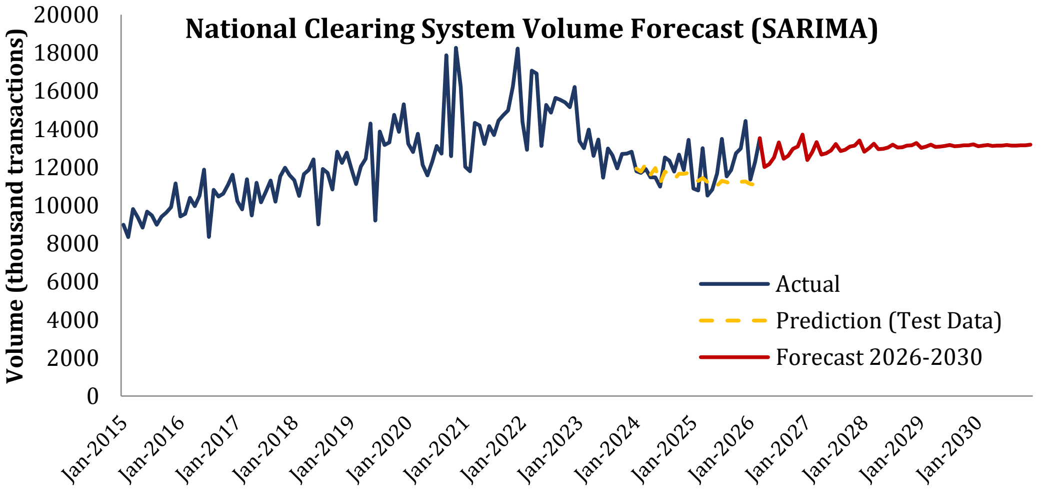
(a) Debit Card (ARIMA)



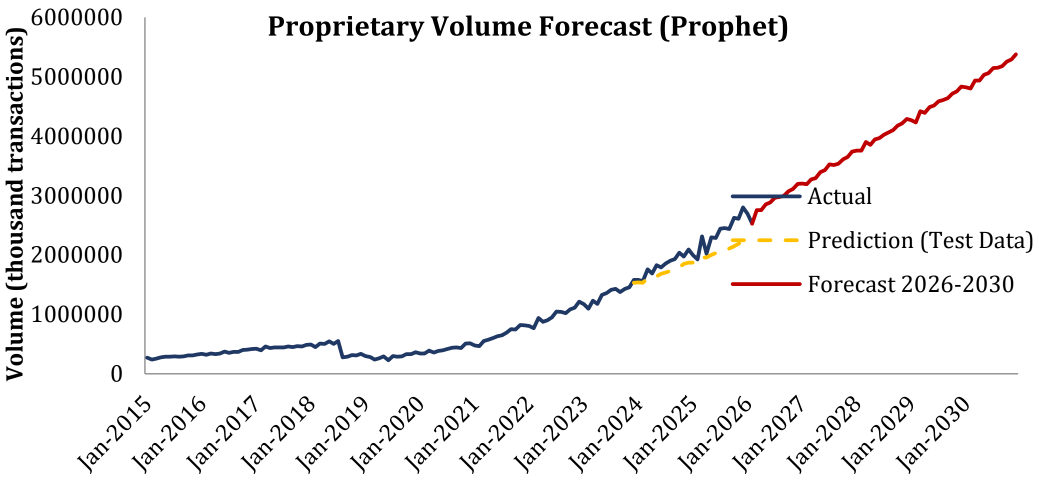
(b) Credit Card (Prophet)



(c) Electronic Money (ARIMA)



(d) National Clearing System (SARIMA)



(e) Proprietary (Prophet)

Figure 3. Volume Forecast Results by Channel, 2026–2030 (Best-Performing Model per Channel)

The best-performing model for each channel was subsequently used to generate volume projections for the 2026–2030 period, from which the compound annual growth rate (CAGR) was computed and used to classify each channel according to product life cycle theory (Levitt, 1965). Table 3 presents these results.

Table 3. Projected CAGR and Product Life Cycle Classification

Channel	Best Model	CAGR 2026–2030 (%)	PLC Stage
Proprietary	Prophet	14.50	Growth
Electronic Money	ARIMA	10.63	Growth
Credit Card	Prophet	8.80	Growth
National Clearing System	SARIMA	0.75	Maturity
Debit Card	ARIMA	0.15	Maturity

Three channels, namely Proprietary, Electronic Money, and Credit Card, are projected to remain in the growth stage, with CAGR ranging from 8.80% to 14.50%, while Debit Card and the National Clearing System are both projected to be effectively flat, placing them in the maturity stage under a 0–3% CAGR threshold. Notably, the National Clearing System is the only channel for which SARIMA, rather than ARIMA or Prophet, is the best-performing model: its SARIMA(0,1,1)(1,0,0,12) specification captures a mild seasonal regularity in the series that the non-seasonal ARIMA specification does not, yielding a lower MAPE (6.99% versus 8.04%) and a projected CAGR of 0.75%, only marginally above the flat trajectory implied by ARIMA. This suggests that whatever structural change previously affected this channel's growth trajectory has already been absorbed into the series by the end of the sample period, with the channel now oscillating around a stable plateau rather than continuing to contract. This illustrates a broader methodological point: allowing seasonal and non-seasonal specifications to compete on equal footing, evaluated by out-of-sample accuracy rather than assumed a priori, lets each channel's best-fitting model reflect its own temporal structure rather than a uniform modeling choice applied indiscriminately across channels.

The resulting classification carries direct strategic implications under product life cycle theory, which prescribes a distinct strategic emphasis for each stage (Levitt, 1965). The three growth-stage channels, Proprietary, Electronic Money, and Credit Card, are those for which continued capacity expansion is likely to yield the greatest returns, consistent with the theory's emphasis on capturing market share while demand is still expanding. However, treating these three channels as strategically identical would overlook meaningful differences in the nature of their growth. Proprietary and Electronic Money are both high-frequency, low-value transaction channels, for which sustained growth places direct pressure on transaction-processing and acceptance infrastructure; for these channels, capacity expansion in the form of additional EDC terminals, network capacity, and system reliability is likely to be the binding constraint on continued growth, rather than consumer demand itself, consistent with evidence that the productive capacity of front-line service infrastructure, rather than aggregate registration, determines the realized growth of high-frequency digital payment channels (Johnen et al., 2023). Credit Card growth, in contrast, is not primarily an infrastructure-scaling problem but a risk-management one: credit-based instruments carry inherent exposure to fraud and unauthorized use regardless of their growth trajectory, and this exposure scales directly with transaction volume, underscoring the importance of continued investment in analytics-based fraud detection capability as transaction volume expands (Seera et al., 2024). Accordingly, while all three growth-stage channels warrant continued investment, the specific form of that investment should differ: an infrastructure-oriented emphasis is more appropriate for Proprietary and Electronic Money, while a security-oriented emphasis is more appropriate for Credit Card.

Table 4. Summary of Channel-Level Strategic Recommendations

Channel	PLC Stage	Strategic Priority	Illustrative Action
Proprietary	Growth	Infrastructure-oriented capacity expansion	Expand EDC terminal network and processing capacity
Electronic Money	Growth	Infrastructure-oriented capacity expansion	Strengthen network capacity and system reliability
Credit Card	Growth	Risk-oriented capacity expansion	Strengthen fraud detection and authorisation risk controls
Debit Card	Maturity	Defensive repositioning (product modification)	Deepen integration with digital banking services
National Clearing System	Maturity	Defensive repositioning (market modification)	Reposition toward higher-value, lower-frequency transaction segments

The two maturity-stage channels, Debit Card and the National Clearing System, instead call for a defensive or repositioning emphasis, focused on sustaining relevance and efficiency rather than pursuing further volume growth. Here too, the two channels differ in the strategic response their maturity warrants. Debit Card remains, in absolute terms, one of the largest channels in the system; its near-zero projected growth is therefore better interpreted as market saturation than as decline, consistent with Levitt's (1965) discussion of product modification as a strategy for extending a mature offering's relevance, for instance through deeper integration with digital banking services rather than functioning as a standalone channel, an approach consistent with evidence that integrated, omnichannel banking experiences strengthen customer engagement and retention (Andino, 2022). The National Clearing System, by contrast, has plateaued at a substantially smaller scale following its earlier structural adjustment, suggesting that its future relevance may depend less on defending its existing retail positioning and more on a deliberate market modification that repositions the channel toward the higher-value, lower-frequency transaction segments for which its batch-clearing mechanism remains comparatively well-suited, rather than competing directly with faster retail alternatives. Table 4 summarizes these channel-level strategic implications, translating each product life cycle classification into a concrete strategic priority and illustrative action.

Taken together, these findings illustrate how forecast-derived growth trajectories can operationalize product life cycle theory at the level of individual payment channels within a single organization's channel portfolio, rather than treating the payment system as a single undifferentiated offering. This channel-level application extends product life cycle theory beyond its conventional use for single products or firms (Hoberg & Maksimovic, 2022) to a portfolio of service delivery channels operated by the same institution, echoing calls in the product portfolio management literature for governance approaches that account for individual products' differing life cycle positions rather than managing a portfolio as a homogeneous whole (Hansen & Svejvig, 2022). This offers a systematic basis for differentiating strategic priorities across channels that share an operator but differ in their growth trajectory and underlying transaction characteristics.

Conclusion

This study compared the forecasting performance of ARIMA, SARIMA, and Prophet across five non-cash retail payment channels in Indonesia and used the resulting projections to classify each channel according to product life cycle theory. The comparison confirms that no single forecasting model performs best universally: ARIMA provided the most accurate projections for two channels (Debit Card and Electronic Money), Prophet performed best for two channels (Credit Card and Proprietary), and SARIMA performed best for the remaining channel (the National Clearing System). Based on projected growth trajectories through 2030, three channels, namely Proprietary, Electronic Money, and Credit Card, were classified as being in a growth stage, while Debit Card and the National Clearing System were classified as being in a maturity stage, with each classification carrying a distinct strategic implication rather than warranting a uniform policy response across channels.

These findings contribute both a methodological comparison relevant to forecasting in the payment systems domain and a theoretically grounded framework for translating forecast outputs into differentiated channel strategy, extending product life cycle theory from its conventional application at the level of a single product or firm to a portfolio of service channels operated by the same institution. This study is limited by its reliance on univariate forecasting models, which do not incorporate potentially relevant exogenous factors such as macroeconomic conditions or payment infrastructure availability; by its focus on transaction volume alone, leaving transaction value projections for future investigation; and by its evaluation of only three forecasting approaches, which does not preclude the possibility that alternative methods, including machine learning-based models, may yield further improvements in accuracy. Future research may extend this framework by incorporating exogenous determinants into the forecasting process itself, by validating the proposed channel-level product life cycle classification against realized strategic outcomes over time, and by examining whether this approach generalizes to payment systems in other emerging market contexts.

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