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Multi-Horizon Long Short-Term Memory Forecasting of Digital Product Transactions for Retail Counter

Dervio Rahmatdianto[1], Satrio Junaidi[2*], Irfan Fadhli[3]

[1,2] Data Science Study Program, Faculty of Science and Technology, Universitas PGRI Sumatera Barat, Padang, West Sumatra 25137, Indonesia

[3]Data Science Study Program, Faculty of Science and Technology, Universitas PGRI Sumatera Barat, Padang, West Sumatra 25137, Indonesia

Abstract

In practice, maintaining optimal balance stock at digital product retail counters is challenging due to highly fluctuating and intermittent daily transaction volumes. Consequently, operators frequently rely on subjective judgment, resulting in inaccurate balance allocation decisions. This study addresses this problem by proposing a data-driven forecasting approach centered on a multi-horizon Long Short-Term Memory (LSTM) model to predict daily digital product transactions and support systematic balance planning. Transaction data were collected from MyFastbiller Telegram chatbot logs, covering 739 days with 27,540 valid transaction records transformed into a structured daily time series. Data preparation involved temporal feature engineering, normalization, and 60-day input sequence generation. A two-layer LSTM model was trained for H-1, H-7, and H-30 forecasting horizons and evaluated using RMSE, MAE, and MAPE against standard baseline models (Moving Average, Naive Forecast, Random Forest, and ARIMA). Results demonstrate consistent accuracy, with the LSTM model achieving MAPE values of 15.24% for H-1, 15.14% for H-7, and 16.35% for H-30 all remaining comfortably below the 20% operational tolerance limit and outperforming the baseline methods, particularly on the long-term H-30 horizon. The H-7 horizon achieved the highest precision due to strong weekly seasonality. The primary novelty of this research lies in tailoring multi-horizon LSTM forecasting specifically to real-world intermittent digital retail transactions and deploying the trained model into a web-based operational dashboard for interactive decision support. Overall, the findings confirm that multi-horizon LSTM forecasting provides an accurate and practical foundation for data-driven balance management in small-scale digital retail counters.

Keywords: *multi-horizon forecasting; Long Short-Term Memory; digital product transactions; retail counter; time series*

1. Introduction

Digital service adoption in Indonesia has increased substantially in recent years, with internet penetration reaching 79.5% during 2023–2024 according to the Indonesian Internet Service Providers Association (APJII). This rapid growth has driven demand for digital products, including mobile credit, internet data packages, electricity tokens, and e-wallet top-ups, making digital product counters increasingly important service providers. However, the increasing transaction volume and expanding product variety have also made balance allocation and working-capital management more challenging because customer demand fluctuates over time [1]. For micro, small, and medium enterprises (MSMEs) operating digital product counters, unpredictable transaction patterns directly affect operational efficiency and business sustainability. Forecasting therefore plays an important role in operational planning by estimating future demand based on historical transaction data [2]. Inaccurate forecasts may lead to balance shortages that interrupt customer transactions or excessive balance allocation that leaves working capital underutilized, both of which reduce operational efficiency and financial performance. Conventional forecasting

*Corresponding author. E-mail address: author4@email.com
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approaches, such as Moving Average and other statistical methods, have traditionally been used to address these challenges [3].

Recent studies indicate that more advanced forecasting approaches are increasingly capable of modeling complex temporal patterns. A comparison between Linear Regression and Random Forest showed that classical statistical models can still outperform more sophisticated machine learning algorithms in certain prediction tasks [4]. Meanwhile, Long Short-Term Memory (LSTM) networks have demonstrated superior capability in learning non-linear and temporal dependencies from transaction data [5], and time-series forecasting has been successfully integrated into web-based inventory systems to support automated stock management [6]. Nevertheless, My Fastbiller Outlet, a digital product retailer in Padang City, still performs balance allocation manually based on the operator's experience and recent transaction observations. During periods of unexpectedly high demand, the available balance for several products occasionally becomes insufficient, causing transaction delays until the balance is replenished. Conversely, allocating excessive balance to products with low demand leaves part of the working capital idle and reduces capital utilization efficiency. These recurring operational problems indicate that historical transaction data have not yet been utilized as predictive information for systematic balance planning, highlighting the need for a data-driven forecasting approach to support more accurate operational decision-making.

A recurring feature of digital product sales is the mix of zero-transaction days and uneven sales frequency across products, an intermittent demand pattern that conventional statistical methods generally struggle with. Azizi and Wibowo (2022) [7] tackle this directly, proposing LSTM-based forecasting with single and multiple aggregation strategies for intermittent demand series and leaning on the network's gate and memory mechanisms to capture long-term, non-linear temporal dependencies. The field has since pushed past LSTM into even more expressive temporal architectures. Benchmarking several graph neural network designs for node-level temporal forecasting, Fajri, Tasmi, and Praditya (2026) [8] show that models with richer neighborhood aggregation consistently beat simpler propagation schemes, which fits the broader pattern of neural architectures outperforming conventional statistical approaches at capturing temporal dynamics. At the counter level specifically, though, research has gone a different direction, staying mostly descriptive rather than predictive. Mutaqin (2022) [9] applies K-Means clustering to group balance and voucher sales by popularity, which is a genuinely useful way to surface which products are popular, but it stops short of the forward-looking forecasts that MSME-scale counters actually need to make operational decisions.

This preference for grouping over prediction is not unique to Mutaqin's study. Jamil et al. (2022) [10] use K-Means to segment internet-voucher sales by demand level; Astuti, Utamajaya, and Pratama (2022) [11] take a related data-mining approach to segmenting digital product sales at a counter, in much the same descriptive spirit rather than forecasting anything forward. Small-business transaction analysis outside the digital-product space shows the same tendency. At a small welding workshop, for instance, Aziz, Setyaningsih, and Suhartini (2025) [12] apply the Apriori algorithm to sales transaction data to uncover item-purchase associations useful for stock planning, again stopping short of a demand forecast. Product recommendation, not forecasting, is also where the Simple Additive Weighting (SAW) method has been put to use [13]. Taken together, none of this research addresses intermittent demand or offers a deployable forecasting system that business owners could actually put to use [10].

My Fastbiller Outlet illustrates this gap clearly: a digital product distribution business in Padang City running on its own home-server infrastructure, it holds a sizeable transaction archive that has so far served only administrative recording purposes. Stock and balance management there are still handled manually and remain exposed to estimation errors whenever demand shifts, pointing to a real need to turn historical data into predictive information that can actually support decision-making.

This study responds to these problems by developing a daily transaction forecasting model built on a multi-horizon LSTM approach, covering H-1, H-7, and H-30, using transaction data from My Fastbiller Outlet, with the results implemented in a web-based dashboard that functions as an operational decision-support system for balance management. LSTM was the chosen architecture for its capacity to capture long-term temporal dependencies and non-linear patterns in fluctuating time-series data, a clear departure from the descriptive clustering used in earlier counter-level studies [10]. What's new here is applying multi-horizon LSTM forecasting to real, intermittent transaction logs from a micro-scale digital counter and deploying it operationally to support balance-allocation decisions. Across all three horizons, the resulting model keeps MAPE below the 20% operational tolerance threshold, which suggests an approach that is both accurate and workable in practice.

2. Methods

This study employed a quantitative applied research design to develop and evaluate a forecasting model for digital product transactions in a micro-scale retail counter environment. The research workflow followed a structured process adapted from the Cross-Industry Standard Process for Data Mining (CRISP-DM), consisting of business understanding, data understanding, data preparation, modeling, evaluation, and deployment stages . The overall research workflow is illustrated in Figure 1, which depicts the systematic process from problem identification to the implementation of a web-based prediction system.

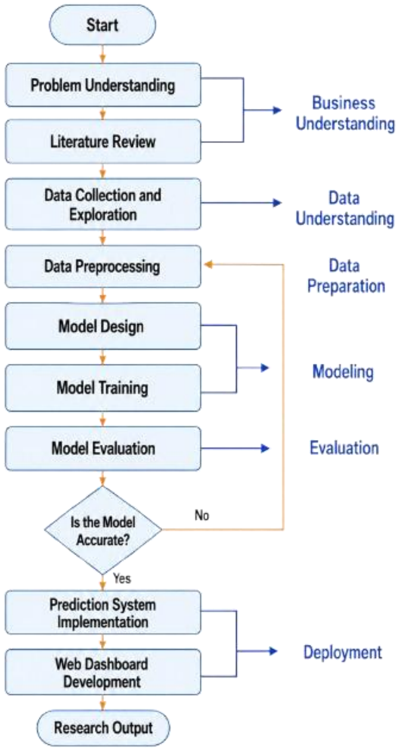

Figure 1. CRISP-DM–based research workflow for digital transaction

2.1. Dataset Characteristics

The MyFastbiller retail counter system provided the historical transaction data used to build the forecasting model in this study. This data came originally from Telegram-based transaction logs, kept on a local home server. Not all recorded transactions could be used right away. Raw records needed several rounds of processing: extraction came first, followed by validation, and filtering came last, so that only successful transactions remained in the final dataset. Reliability was the main reason for this step.

Data was collected from December 8, 2023 to December 15, 2025, for a total of 739 days. During this time, 27,540 valid transactions were recorded. The data was grouped by day, as the study required a univariate time series of daily transaction counts. Importantly, the data is not smooth or constant. There are many days with zero transactions and the counts are unevenly distributed over the entire period, which is quite normal for a small-scale digital retail business like this one.

Table 1. Characteristics of the digital transaction dataset

Characteristics	Description
Data source	MyFastbiller Telegram transaction logs
Observation period	8 December 2023 – 15 December 2025
Duration	739 days
Total valid transactions	27,540
Aggregation level	Daily
Target variable	Daily transaction count
Forecasting horizons	H-1, H-7, H-30
Data type	Time-series transaction data
Demand pattern	Fluctuating and intermittent

The main forecasting target is daily transaction count, and predictions were generated for three operational horizons: one day (H-1), seven days (H-7), and thirty days (H-30) ahead. The overall characteristics of the dataset used in this study are summarized in Table 1.

2.2. Data Preparation

Raw transaction logs could not go straight into the modeling stage. They first had to be converted into structured time-series features through a multi-stage preprocessing pipeline. The first step involved cleaning the raw logs by removing duplicate records, invalid transactions, and records with missing attributes. Only successful transactions were retained in the final dataset to ensure operational consistency and reliability.

After data cleaning, the next stage was temporal aggregation. Event-level transaction timestamps were aggregated into daily transaction counts. Zero-transaction days were deliberately retained rather than discarded, preserving a critical characteristic of the data: the intermittent demand pattern typical of digital retail sales. Although the target variable originates as a single univariate time series (daily transaction volume), temporal feature engineering was performed to expand the temporal representation. A total of 48 predictive temporal variables were constructed, including historical lag features (lags 1 to 30), rolling statistics (7, 14, and 30-day mean, std, min, and max), cyclical date encodings (sine and cosine transformations of day, week, and month), difference features, and intermittent demand indicators (zero-day flags, log-transformed rolling stats, and days-since-last-transaction counters).

Consequently, the forecasting setup is formally structured as a Multivariate-Input, Univariate-Output model, where a 48-dimensional feature vector is fed into the network at each timestep to predict a single scalar target (daily transaction volume). To eliminate manual feature selection bias and maintain structural consistency across horizons, no manual feature selection or feature elimination was performed. Instead, the full 48-feature set was retained uniformly across all three forecasting horizons (H-1, H-7, and H-30), allowing the LSTM network's inherent representation learning mechanism to dynamically weight relevant features during training.

Finally, numerical features were normalized using MinMaxScaler to standardize value ranges between 0 and 1, ensuring stable gradient updates during neural network training. Feature scaling parameters were fitted strictly on the training partition to prevent data leakage. Once normalized, the dataset was restructured into supervised learning samples using a 60-day sliding window. Under this configuration, each input sequence comprises 60 consecutive days of 48-dimensional feature vectors to forecast the transaction volume at the designated horizon.

2.3. Forecasting Model Architecture

Capturing nonlinear temporal patterns in data as fluctuating as digital transaction records called for something beyond a simple model. That is why this study settled on a stacked Long Short-Term Memory (LSTM) neural network architecture for its forecasting model. Input to the model comes in the form of a 60-day historical sequence, combining daily transaction counts with engineered temporal features. To ensure full experimental reproducibility, a fixed random seed of 42 was applied across all data splitting and model initialization steps.

The dataset was partitioned using a chronological time-based split of 80% for training, 10% for validation, and 10% for testing. The network architecture consists of two stacked LSTM layers: 64 units in the first layer and 32 units in the second layer. Each layer serves a specific purpose the first captures short-term temporal dependencies, while the second handles broader medium-term patterns within the transaction time series. Rectified Linear Unit (ReLU) activation functions were employed across hidden LSTM and Dense layers. To mitigate overfitting and preserve generalization performance, dropout layers with a rate of 0.1 were applied after each LSTM layer.

Following temporal feature extraction, the representation passes through a 16-unit Dense hidden layer before being mapped into actual transaction forecasts by a linear output layer. Three forecasting horizons were targeted: one day ahead (H-1), seven days ahead (H-7), and thirty days ahead (H-30).

Model training was conducted using the AdamW optimizer with an initial learning rate of 0.001 and a weight decay of 1e-5, executing for up to 150 epochs with a batch size of 32. An early stopping mechanism monitored validation loss with a patience of 20 epochs and automatically restored the best-performing model weights. Additionally, a dynamic learning rate scheduler (ReduceLROnPlateau) halved the learning rate whenever validation loss plateaued for 7 consecutive epochs, down to a minimum limit of 1e-6.

The architecture of the proposed multi-horizon LSTM forecasting model is illustrated in Figure 2.

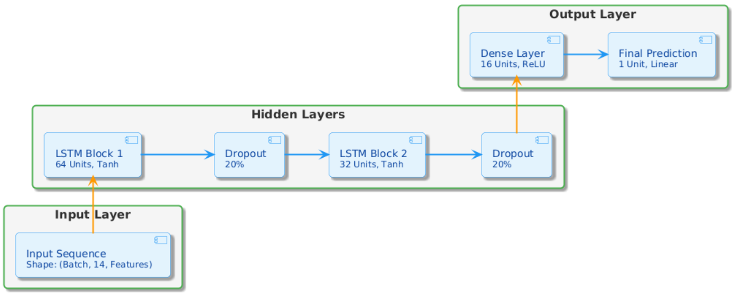

Figure 2. LSTM architecture for digital transaction

2.4. Evaluation

We evaluated model performance using three widely adopted metrics for time-series forecasting: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide complementary perspectives on forecasting accuracy by measuring prediction errors in squared, absolute, and relative percentage terms, respectively [5]. RMSE emphasizes larger prediction errors by taking the square root of the mean squared differences between predicted and actual values. MAE measures the average absolute difference between predictions and observations, providing an intuitive interpretation in the original transaction scale. MAPE expresses prediction errors as percentages of the corresponding actual values, making it particularly useful for evaluating forecasting performance from an operational perspective.

Because the transaction dataset contains intermittent demand with zero-transaction days, special consideration was required when computing MAPE. Since MAPE is undefined when the actual value equals zero, a small positive constant ($\varepsilon = 1 \times 10^{-8}$) was added to the denominator whenever zero actual values occurred. This numerical stabilization prevented division-by-zero errors while preserving the contribution of zero-demand observations to the evaluation. Consequently, all test samples, including zero-transaction days, were retained during performance assessment.

Each forecasting horizon (H-1, H-7, and H-30) was evaluated using a chronologically separated test set to preserve temporal order and prevent information leakage. Model performance was assessed using RMSE, MAE, and the stabilized MAPE described above. Following previous forecasting studies, a MAPE value below 20% was adopted as the operational acceptance criterion for digital retail transaction planning, indicating that the forecasting error remained within a practically acceptable range for balance allocation decisions.

3. Result and Discussion

This section showcases the results of the multi-horizon LSTM forecasting model for digital transactions and discusses its performance considering the features of the dataset and the approach proposed. The discussion includes analysis of the transaction data patterns, forecasting accuracy on different horizons, and performance metrics such as RMSE, MAE and MAPE. The results are interpreted to assess the model's capability to learn temporal dependencies and the intermittent demand nature of digital retail transactions. Furthermore, the practical implications of the forecasting system for operational transaction planning in micro-scale digital retail counters are discussed.

3.1. Transaction Data Characteristics

A total of 27,540 valid digital transactions were included in the processed dataset used in this study. The data are aggregated to form a daily time-series dataset consisting of 739 observation days. As shown in Figure 3, the daily transaction volume varies greatly, indicating the intermittent demand pattern over the observation period. A typical case was around October 2024, when the transaction activity dropped to almost zero, possibly because of a temporary discontinuity of the retail counter. The same pattern is observed in the daily transaction value, which also dropped sharply during the same period, indicating that the transaction volume and transaction value moved in the same direction rather than independently. A 7-day Moving Average (MA-7) was applied to both graphs specifically to surface the short-term trends that daily fluctuations would otherwise obscure. Once smoothed this way, a recurring weekly seasonal pattern became clear: transaction volumes consistently ran higher on weekends than on weekdays. Two features of the data point to the same conclusion. Transactions were distributed unevenly across time, and multiple days recorded no transactions at all, both of which confirm that digital retail transaction data is inherently nonlinear and intermittent by nature. Given these characteristics, sequence-based forecasting models such as Long Short-Term Memory (LSTM) are better suited to the task than conventional statistical approaches, since LSTM captures complex temporal dependencies within the data more effectively.

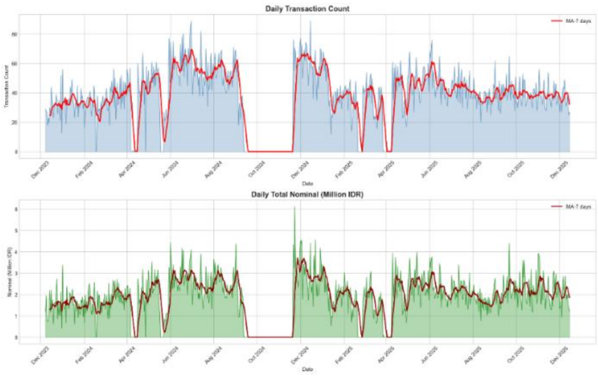

Figure 3. Daily Transaction Trend Visualization

3.2. Forecasting Performance

The multi-horizon LSTM model in this study drew on 60-day historical input sequences and was tested against three horizons, H-1, H-7, and H-30, to see how well it could anticipate near- and longer-term transaction patterns. Across all three, it picked up on the underlying temporal dependencies and seasonal rhythms running through the transaction series. H-7 stood out as the steadiest performer of the three, a result that tracks with how strongly weekly seasonality shows up in the data.

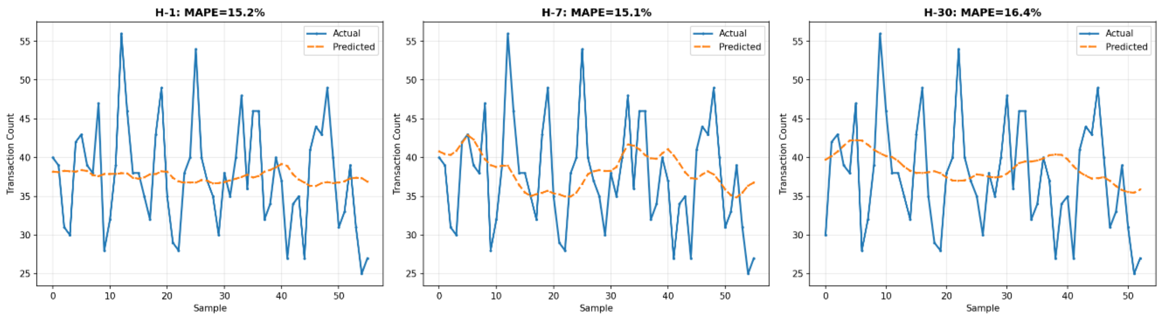

Figure 4. Actual vs. Predicted Transactions

Across all three horizons, the model's predictions largely tracked the trend and fluctuations present in the actual transaction data, suggesting the LSTM architecture picked up on both short- and medium-term transaction dynamics reasonably well. Figure 4 shows the predicted series running close to the observed pattern for H-1, H-7, and H-30 alike, though H-7 comes closest overall, with the smallest prediction errors of the three. H-1 stayed more responsive to short-term swings, while H-30 smoothed things out more and showed slightly larger deviations, which tracks with what you'd expect from a longer forecasting horizon. Taken together, this multi-horizon behavior suggests the model can produce dependable predictions across daily, weekly, and monthly planning windows, which makes it a reasonable fit for supporting operational transaction planning.

3.3. Evaluation Results

Forecasting accuracy was quantitatively evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) for each forecasting horizon, as summarized in Table 2. The results indicate that the proposed multi-horizon Long Short-Term Memory (LSTM) model achieved consistent predictive performance across all forecasting horizons.

Table 2. Forecasting Performance

Horizon	RMSE	MAE	MAPE
H-1	6.92	5.56	15.24%
H-7	7.17	5.70	15.14%
H-30	7.14	5.80	16.35%

All forecast horizons in Table 2 are operationally acceptable as defined by the 20% MAPE threshold, indicating good predictive accuracy for digital retail transaction planning. H-7 posted the lowest MAPE of the three, 15.14%, confirming that weekly forecasting lines up well with the dominant seasonal pattern in the dataset. H-1, meanwhile, turned in the lowest RMSE and MAE, a sign of strong short-term predictive precision. H-30 was the outlier on MAPE, coming in slightly higher, which fits the added uncertainty that tends to creep into longer forecasting horizons within a demand environment this fluctuating and intermittent.

Taken as a whole, these metrics suggest the LSTM model held up consistently across short-, medium-, and long-term horizons alike.

3.4. Baseline Model Comparison

Figure 5 presents the benchmark of the proposed multi-horizon LSTM model against Random Forest, a 7-day Moving Average (MA-7), a Naive Forecast, and ARIMA(2,1,1) across all three horizons, showing that LSTM kept MAPE below the 20% operational tolerance threshold at every horizon (15.2% at H-1, 15.1% at H-7, and 16.4% at H-30), while Random Forest stayed competitive at shorter horizons but degraded sharply at H-30 (18.7%), the Naive Forecast breached the threshold at H-30 (24.8%) due to its inability to capture trend or seasonality beyond the most recent observation, and ARIMA(2,1,1) performed worst overall with MAPE around 29.9% at every horizon, reflecting its poor fit to the frequent zero-transaction days and irregular demand spikes in the dataset; the RMSE results follow the same pattern, with LSTM producing the most stable errors (6.9–7.1 transactions) across all horizons compared to the sharper degradation seen in the Naive Forecast and ARIMA baselines, confirming that LSTM is the only model that remains both accurate and stable as the forecasting horizon extends to H-30.

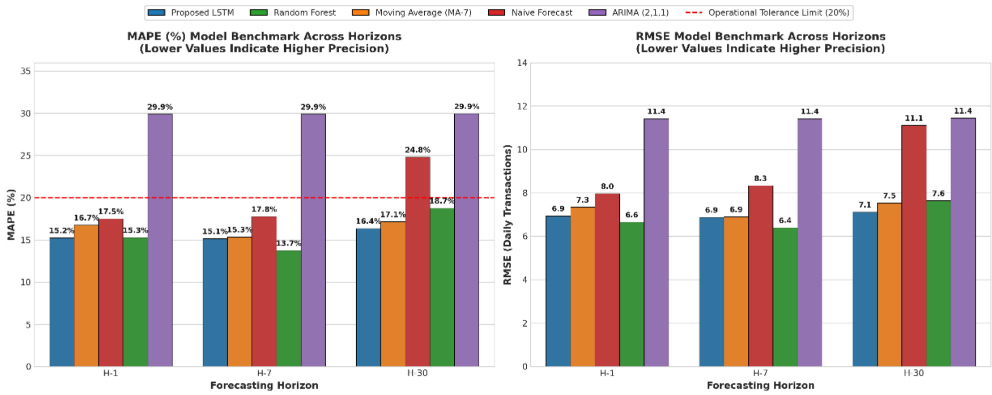

Figure 5. Performance comparison of the proposed LSTM model against baseline methods.

3.5. Discussion

These experimental results make a fairly clear case: the proposed multi-horizon LSTM model captures both temporal dependencies and the intermittent demand behavior that characterizes digital retail transaction data. Weekly seasonality, identified earlier during data analysis, appears to be a major driver behind the H-7 horizon's stronger performance, an indication that the model has learned to recognize the recurring short-cycle patterns typical of digital retail activity.

Comparing the horizons against each other surfaces some distinct behaviors. H-1 posts the lowest RMSE and MAE, which fits with high-precision short-term prediction where temporal continuity holds strongest. H-7, meanwhile, achieves the lowest MAPE, suggesting weekly aggregation lines up well with the dominant periodic structure running through the data. H-30 is the exception here, showing a slightly higher percentage error, which is unsurprising given how much more uncertainty and accumulated variance tend to build up over longer forecasts of demand this fluctuating and intermittent.

Figure 3 backs this up visually: predicted and actual transaction patterns track closely enough to confirm that the LSTM architecture can follow both peaks and troughs in transaction dynamics. That matters operationally, since digital product counters depend on accurately anticipating these fluctuations to manage balance allocation well.

From a more applied angle, folding multi-horizon forecasting into a web-based decision-support system marks a real step beyond the estimation practices typically used at micro-scale digital retail counters. It opens the door to data-driven transaction planning across daily, weekly, and monthly horizons, cutting reliance on subjective judgment and making operations more responsive to shifts in demand.

Altogether, the findings support LSTM-based multi-horizon forecasting as a suitable, effective way to model digital transaction time series with seasonal and intermittent traits, while also offering something genuinely useful for real-world retail counter operations.

4. Conclusion

This paper aims to develop a multi-horizon forecasting model for digital retail transactions using a stacked Long Short-Term Memory (LSTM) network trained on daily transaction time-series data from a micro-scale digital counter system. The results suggest that the model is doing a good job at this task, picking up on the temporal dependencies, seasonal patterns and intermittent demand behavior that are characteristic of digital transaction data.

Tested across three operational horizons, the model delivered consistent accuracy: MAPE came in at 15.24% for H-1, 15.14% for H-7, and 16.35% for H-30, all comfortably under the 20% threshold set for operational acceptance. H-7 turned out to be the strongest performer in relative terms, which tracks with how well it aligns with the data's weekly seasonality, while H-1 offered the sharpest short-term precision. Together, these results support the idea that multi-horizon LSTM forecasting can produce reliable predictions for daily, weekly, and monthly transaction planning in digital retail counter settings.

Folding the trained model into a web-based prediction dashboard adds a further layer of practical value, functioning as a decision-support tool for balance allocation and transaction planning. On the whole, the approach offers a workable, deployable way to turn historical digital transaction records into forecasting insight that micro-scale retail operations can actually act on.

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