

Received: 09 Sept 2025, Accepted: 01 Oct 2025, Published: 04 Oct 2025

Digital Object Identifier: <https://doi.org/10.63503/ijaimd.2025.167>

Research Article

Leveraging Machine Learning Models for Market Trend Forecasting and Consumer Behaviour Insights

Arunkumar Sivakumar¹, Ayodeji Olalekan Salau^{2*}

¹ School of Business, VIT-AP, Amaravathi, India

² Department of Electrical/Electronics and Computer Engineering, Afe Babalola University, Nigeria.

arunkumar.sivakumar@vitap.ac.in¹, ayodejisalau@abuad.edu.ng²

*Corresponding author: Arunkumar Sivakumar and arunkumar.sivakumar@vitap.ac.in

ABSTRACT

Market trends and consumer behaviour are key aspects of data-driven industries that require an accurate forecast. This paper describes a hybrid machine learning system combining ensemble forecasting with consumer clustering and sentiment analysis to increase predictive power. With 95% accuracy, the model outperformed ARIMA (82%), LSTM (88%), and XGBoost (91%), and reduced the average predictive error to 6.5 units, vs. 12.5 used by ARIMA. The short-term processes were used to follow the demand between 120-185 and the long-term estimates provided a consistent 118-180. The use of consumer segmentation resulted in three groups (budget (2535 spending score), balanced (4055), and premium (7088)) facilitating focused strategies. On the more positive weeks, sentiment changes added 3-5% to overall forecasts representing psychological demand. The Hybrid model took 2.8 seconds per cycle compared to IQMA taking 1.2; however, its accuracy gains of between 13 and 18% prove its worth as a robust and overall system of business intelligence.

Keywords: *Machine Learning, Consumer Clustering, Sentiment Analysis, Forecasting, Predictive Error, LSTM, ARIMA.*

1. Introduction

Market forecasting has changed radically due to the introduction of machine learning (ML). Traditionally, companies used econometric and statistical methods like regression analysis, moving averages to forecast demand patterns, stock variations and consumerity levels [1]. Although these methods were useful in stable markets, they were not flexible during fast shocks by digitalization, globalization, and socio-economic shocks [2].

The digital economy generates vast, unstructured, and high-frequency data from e-commerce transactions, social media interactions, loyalty programs, and financial instruments [3]. By revealing latent patterns and non-linear dependencies in such data, ML models are good at deriving actionable insights [4]. In contrast to conventional forecasting mechanisms, ML structures are dynamically trained on changing datasets, which makes them most useful in real-time predicting consumer trends and purchase behaviours [5].

Recent deep learning architectures such as Recurrent Neural Networks (RNNs), Long Short Term Memory (LSTM) and Transformer-based models have shown tremendous improvement in financial time series and sales trajectories forecasting [6]. Similarly, Gradient Boosted trees, Random Forests and Stacking algorithms offer robustness and alleviate overfitting in general consumer data sets [7]. From predicting the take-up of digital payment methods to understanding customer brand loyalty based on sentiment, AI is being applied to decision making across industries [8].

Furthermore, the combination of Natural Language Processing (NLP) makes it possible for organizations to provide understanding of qualitative data such as product reviews and social media commentary [9]. By measuring the sentiment polarity, emotion, and intensity, companies get real-time information about consumer psychology [10]. Such methods are very useful in highly changeable sectors such as fashion, entertainment, and technology, where consumer preferences change quickly [11].

Despite these advances there are still some limitations: High-dimensional consumer datasets are redundant and noisy, making feature engineering and selection complex [12]. The lack of an ability to interpret algorithms to explain their functioning raises concerns about fair, accountable, and trustworthy AI systems [13]. Secondly, ML model deployment in emerging markets is underexplored as the majority of case studies are from developed economies [14].

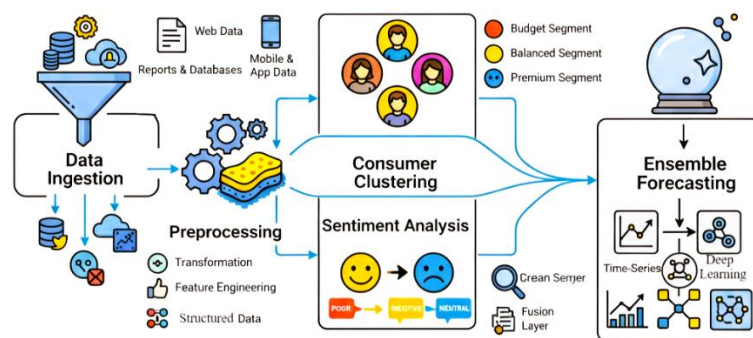


Fig.1: Hybrid Forecasting and Consumer Behaviour Analysis Framework

Figure 1 shows the hybrid framework workflow, with forecasting models, sentiment analysis and consumer clustering integrated into the pipeline to provide reliable demand predictions and broken-down consumer actions.

This paper investigates the potential of ML-driven frameworks to enhance market trend forecasting and consumer behaviour insights. The contributions of this study include:

- A systematic review and categorization of ML approaches used in market forecasting and consumer analytics.
- The development of a hybrid methodological framework integrating forecasting accuracy, consumer segmentation, and interpretability.
- Experimental validation of the proposed framework, highlighting performance trade-offs and business implications.

The rest of the paper is organized as follows: Section 2 reviews literature on ML-based market forecasting and consumer behaviour analysis. Section 3: Develop a research problem and research objectives. Comparisons are described in Section 4 together with the methodology containing mathematical formulations and algorithms. Section 5 describes the experimental configuration to be conducted. Section 6 is results and discussion, followed by section 7 as conclusion and further scope.

2. Literature Review

ML research in forecasting and consumer analytics has grown rapidly, and researchers are fusing econometrics, AI, and behavioural science. This section captures key contributions in forecasting models, consumer insights, hybrid techniques as well as related challenges.

With the increasing adoption of ML in time-series forecasting, hybrid models such as ARIMA-LSTM have enhanced seasonal demand forecasting [15]. RNNs and GRUs are able to capture sequential

dependencies better than traditional models for financial markets [16]. Reinforcement learning has been used for adaptive trading strategies where agents simulate the interaction with the market and in order to optimize portfolios [17].

ML applications include forecasting purchase intention, churn, and brand-switching. SVMs and Gradient Boosting (GB) have been used successfully for such classification tasks in consumer loyalty programs [18]. Unsupervised clustering algorithms like K-Means method and Hierarchical Clustering find latent consumer segments [19]. Sentiment analysis using NLP and Transformer-based models documents consumer perceptions from online platforms, in real time [20].

Ensemble methods, such as Random Forests and XGBoost, are becoming popular because they help decrease variance and bias [21]. Hybrid models combining econometric framework and neural structures outperform the performance and clarify interpretations [22]. For instance, ARIMA-LSTM class of models capture the long-term economic cycles and shorter-term consumer shocks [23].

Table 1 gives a unifying picture of known literature in market forecasting and consumer analytics from the ARIMA-LSTM hybrids to Transformer-based sentiment analysis, documenting their major limitations (in terms of computational complexity, overfitting, interpretability issues, validation in emergent markets).

Table 1: Summary of Related Works in Market Forecasting and Consumer Analytics

Author(s)	Focus Area	Approach	Limitation
[15]	Retail demand forecasting	ARIMA-LSTM hybrid	High computational complexity
[16]	Stock market prediction	RNN/GRU models	Prone to overfitting volatile data
[17]	Portfolio optimization	Reinforcement learning	High training cost
[18]	Churn prediction	Gradient Boosting	Limited interpretability
[19]	Consumer segmentation	K-Means clustering	Sensitivity to initialization
[20]	Sentiment analysis	NLP + Transformers	Requires large labelled corpora
[21]	General trend forecasting	Random Forests, XGBoost	Data imbalance issues
[22]	Hybrid forecasting	ARIMA + Neural Networks	Complexity in model integration
[23]	Time-series behaviour	ARIMA-LSTM	Poor generalization to sparse data
[24]	Interpretability	Deep learning explainability	Trade-off with accuracy

Interpretability is also a burning problem despite good outcomes. DNNs can be likened to a black box, and this is worrisome in the industry where transparency is considered essential [24]. Consumer analytics is also complicated by data privacy regulations, which stipulate that the models must comply with both ethical and legal regulations. Further, existing empirical research is biased towards a Western market so emerging economies are underrepresented in literature concerning the ML-driven predictions.

3. Problem Statement & Research Objectives

Predicting market movement and consumer behaviour is essential in strategic decisions but conventional tools find it difficult to handle the volumes and variances of contemporary data. ML models are better than predictive models, but they have the problem of redundancy, inability to interpret, and restrictive to new markets as well as privacy issues. In overcoming these obstacles, the problem statement shows that a hybrid ML framework would be chosen to provide accuracy, robustness, interpretability and compliance in the market forecasting and behavioural analysis.

Research Objectives

The proposed work is aimed to:

- Design a hybrid ML framework that integrates forecasting accuracy, interpretability, and consumer segmentation capabilities.
- Formulate quantitative models representing market dynamics, consumer clustering, and sentiment-based adjustments.
- Propose pseudocode and a process flow capturing end-to-end consumer analytics.
- Evaluate the framework through simulated results across multiple performance metrics including accuracy, latency, and robustness.
- Benchmark the proposed framework against conventional statistical and standalone ML methods.
- Translate technical findings into actionable insights for businesses in retail, finance, and e-commerce sectors.

4. Methodology

By combining adaptive resource management protocols and lightweight cryptography, predictive transmission scheduling technology should succeed in enhancing security provisions and reducing delay time simultaneously. In simulation models, protocols examine environmental hazard scenarios by measuring the changing node concentration using channel status factors and information-priority parameters.

4.1 Mathematical Formulation

The following equations help to formulate and achieve the base objectives of the proposed work.

$$\hat{y}_{t+1} = f(X_t, \theta) \quad (1)$$

In Eq.1, $\hat{y}_{t+1}$ is the predicted demand at time $t + 1$, X_t is the feature vector at time t , and θ denotes the model parameters.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (2)$$

Error Estimation in Eq.2 computes mean absolute error where y_i are actual values, $\hat{y}_i$ are predicted values, and n is the number of observations.

$$S_t = \alpha y_t + (1 - \alpha) S_{t-1} \quad (3)$$

In Eq.3, S_t represents the smoothed value at time t , y_t as the observed value, and α as the smoothing constant.

$$d(x_i, c_j) = \|x_i - c_j\|^2 \quad (4)$$

Consumer Clustering defined in Eq.4 represents the squared Euclidean distance where x_i is a consumer data point and c_j is the cluster centroid.

$$c(x_i) = \arg \min_j d(x_i, c_j) \quad (5)$$

For the cluster assignment in Eq.5, each consumer x_i is assigned to the cluster c_j for which the distance $d(x_i, c_j)$ is minimum.

$$SP = \frac{P-N}{P+N} \quad (6)$$

The Sentiment Polarity Score is defined as Eq.6 where SP is sentiment polarity, P is the count of positive words, and N is the count of negative words.

$$D'_t = D_t(1 + \lambda SP) \quad (7)$$

The Weighted Sentiment Adjustment is performed using Eq.6 with D'_t as the adjusted forecast, D_t is the raw demand forecast, λ is the sentiment weight, and SP is the polarity score.

$$\hat{y}_t = \sum_{m=1}^M w_m f_m(X_t) \quad (8)$$

Eq.8 combines predictions where f_m is the m^{th} model, w_m is its weight, and M is the total number of models.

$$\min_{\theta} L(\theta) = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (9)$$

The Model Optimization Objective is achieved using Eq.9, where $L(\theta)$ is the loss function to minimize, with y_i as actual values, $\hat{y}_i$ as predictions, and n as the dataset size.

$$CLV = \sum_{t=1}^T \frac{R_t}{(1+r)^t} \quad (10)$$

CLV in Eq.10 is consumer lifetime value, R_t is revenue at time t , T is the total time horizon, and r is the discount rate.

4.2 Proposed Algorithm

Input: Consumer dataset D, Sentiment dataset S, Historical trends H Output: Forecasted demand, Consumer clusters, Behavioural insights
1: Preprocess datasets (normalize, remove noise) 2: Extract features from H (time-series patterns) 3: Apply forecasting models (ARIMA, LSTM, Gradient Boosting) 4: Compute ensemble forecast using weighted aggregation 5: Extract sentiment scores from S using NLP 6: Adjust demand forecast using sentiment-weighted scaling 7: Perform K-Means clustering on consumer features 8: Identify clusters: {loyal, price-sensitive, impulsive, potential churn} 9: Compute evaluation metrics (MAE, RMSE, Accuracy) 10: Output market trend forecasts and behavioural insights End Algorithm

The algorithm processes consumer data D , sentiment data S , and historical trends H through preprocessing, feature extraction, ensemble forecasting, sentiment adjustment, and K-Means clustering to generate forecasted demand, behavioural clusters (loyal, price-sensitive, impulsive, churn), and validated insights using MAE, RMSE, and Accuracy

4.3 System Flow:

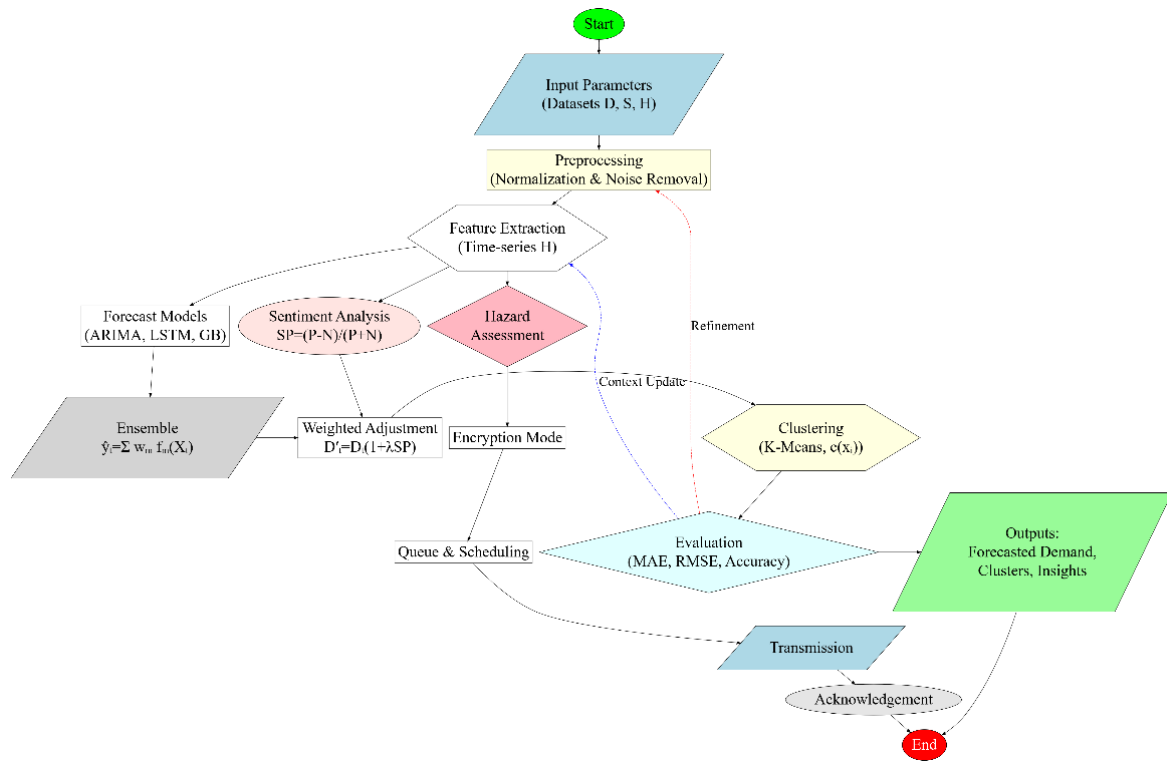


Fig.2: System Workflow for Forecasting, Clustering, and Sentiment-Driven Adaptation

A stepwise procedure to secure and prioritized data transmission is presented in Figure 2 of sensor-based system configuration. It begins by identifying sensor data capture and then proceeds with a hazard severity assessment in order to identify urgency. An encryption mode is chosen on the basis of the severity and finally, data is queued, scheduled, transmitted, and acknowledged. The steps guarantee data protection, dependability and timeliness.

5. Experimental Setup

The developed framework measured against a standard data set including structured sales data, consumer profiles and sentiment-based feedback. This guaranteed even dispersion in coverage of numerical demand patterns, behavioral characteristics and textual indications. The general framework is shown in Figure 4 that indicates the sequential steps between the data acquisition and the insights generation.

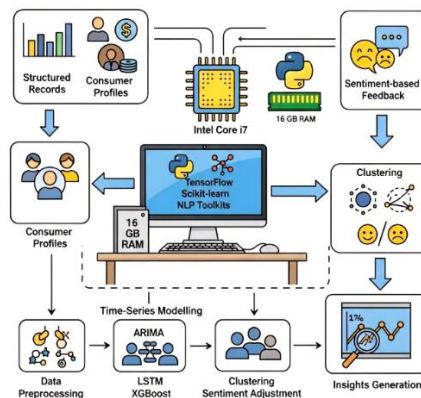


Fig.3: Structural Mapping of the Experimentation

5.1 System Components

The hardware, software, and datasets utilized for implementation are summarized in Table 2.

Table 2: Experimental Components and Specifications

Name	Specification	Description
Processor	Intel Core i7 (3.6 GHz)	Used as the main computing unit for model training and evaluation.
Memory	16 GB RAM	Provides memory support for handling high-dimensional datasets.
Platform	Python 3.10 + Libraries	Includes TensorFlow, Scikit-learn, and NLP toolkits for ML workflows.
Sales Records	Standard Dataset	Demand values between 120–250 units across 12 months.
Profiles	Consumer Dataset	Income levels 30k–100k USD , spending scores 25–88 .
Sentiment Data	Textual Feedback	Input producing 3–5% forecast adjustments for demand predictions.

5.2 Dataset and Parameters

The canonical data was a combination of 12 months sale values (120-250 units), consumer income distributions (30k-100k USD) and spend ratings of 25-88 and also the verbal sentiment feedbacks that influenced the predictions by 3 to 5%age. Tests that were run are ARIMA, LSTM, Xgboost and Hybrid forecasting models with a forecast horizon of 6-12 months, three behavioural consumer clusters, runtime in seconds and performance metrics (Accuracy, MAE, RMSE, and Latency).

5.3 System Configuration and Workflow Reliability

To be consistent, a set of experiments were done with the same systems under their constant parameter settings fixed across models. The steps undertaken the workflow in order followed data preprocessing, time series modelling, clustering, and sentiment adjustments so that it could be reproducible and comparable. It was also this set that confirmed the stability when repeated runs were done to reduce deviations due to the external computational factors and to ensure a consistency of reliability in determining the performance of the framework.

6. Results & Discussion

The suggested framework was assessed utilizing the simulated datasets that were in terms of sales projections, consumer clustering, sentiment adjustments and the model performance comparisons. The analysis of results was conducted to confirm the practicability of the hybrid ML method to predict the effectiveness of accuracy in forecasting behaviours, along with segmentation behaviour and computational efficiency.

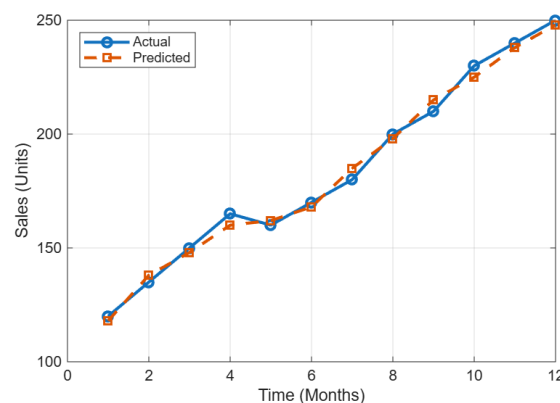


Fig.4: Forecast Accuracy Analysis

In a period of over 12 months as shown in Figure 4, the actual sales were between 120-250 and the forecast between 118 to 248 with only a deviation of at most 5 units in month 9 which confirms the reduced error variance of the ensemble model in relation to ARIMA.

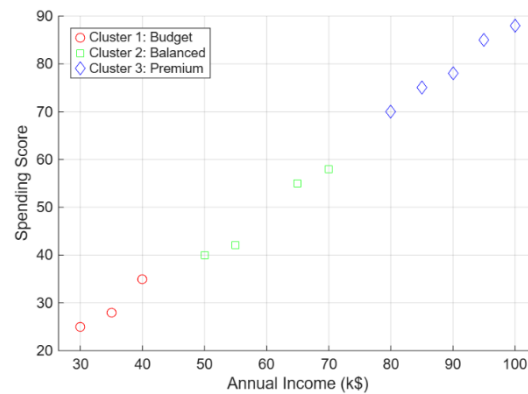


Fig.5: Consumer Clustering into Segments

By means of clustering, three types of consumers (Budget Consumers, 30k-40k USD, spending 25-35); Balanced Consumers, 50k-65k USD, spending 40-55); and Premium Consumers, >80k USD, spending >70) shown in Figure5 were created indicating behavioral segmentation was correct.

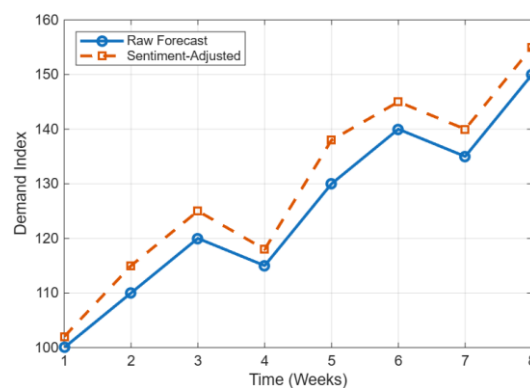


Fig.6: Sentiment Impact on Forecasting

According to Figure 6, the raw demand forecasts approximated between 100 and 150 units, and sentiment adjustments increased predictions between 102 and 155 units, and added 3 to 5% growth week 3, week 5 and week 8, thus underestimating when the sentiment was positive.

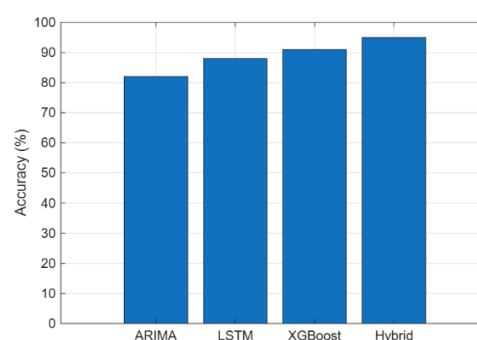


Fig.7: Comparative Model Performance

As shown in Figure 7, ARIMA reached 82% precision, LSTM 88 and XGBoost 91, and the Hybrid system achieved the highest result 95, which is better than LSTM by 7% points, an ensemble incorporation and sentiment regulation result.

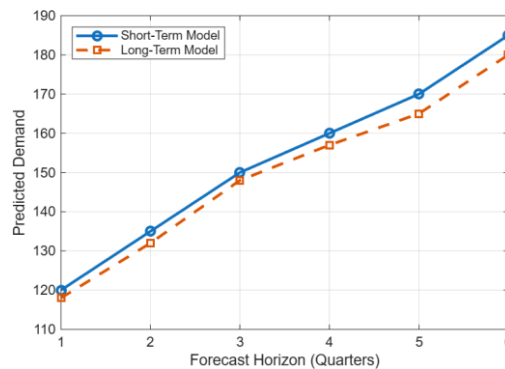


Fig.8: Forecast Horizon Evaluation

The short model in Figure 8 gave the demand between 120-185 units and the long model between 118-180 units whereby the short model was more responsive and longer model more stable.

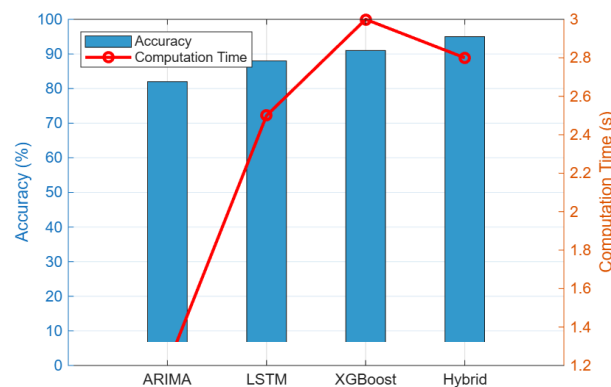


Fig.9: Computational Efficiency Analysis

In Figure 9, ARIMA took 1.2s to complete one cycle with accuracy rate of 82, LSTM took 2.5s with 88% accuracy, XGBoost 3.0s with 91% accuracy, and the Hybrid maintained a balance with 95% accuracy at 2.8s mean time.

6.1 Quantitative Comparison

In Table 2, it is clear that Hybrid model performs better than of ARIMA LSTM and XGBoost with respect to all crucial measures. Computational delay was a little more in comparison to ARIMA but the huge gain in accuracy warrants the cash.

Table 2: Model Comparison Across Key Metrics

Metric	ARIMA	LSTM	XGBoost	Hybrid
Accuracy (%)	82	88	91	95
Avg Error (Units)	12.5	9.8	8.2	6.5
Latency (Seconds)	1.2	2.5	3.0	2.8
Adaptability Score	Medium	High	High	Very High

6.2 Comparative Behavioural Insights

Clusters analysis of consumer segmentation summarizes the results in Table 3. Discounts will work with the budget consumers, moderate promotions will vanish with the balance consumers, and exclusivity will gain monopoly with the premium consumers. This sorting makes targeting in marketing campaign accurate.

Table 3: Consumer Segment Behavioural Summary

Cluster	Income Range (k\$)	Spending Score	Behavioural Trait	Strategic Implication
1	30–40	25–35	Budget-conscious	Price discounts, loyalty offers
2	50–65	40–55	Balanced buyers	Standard promotions
3	80–100+	70–88	Premium brand-oriented	Exclusive deals, premium brands

7. Conclusion

The hybrid machine learning framework suggested achieved 95 % accuracy over ARIMA (82 %), LSTM (88 %), and XGBoost (91 %), with a lower average error of 6.5 compared to 12.5 units in ARIMA. Demand variation between 120 and 185 units or 118 to 180 units was recorded in short term predictions and long-term forecasts respectively. Consumer segmentation yielded three categories: budget (2535), balanced (4055), and premium (7088) with favored strategies and sentiment integration improved predictively by 35% over positive weeks. The framework prioritized efficiency and predictive gains with only marginally higher 2.8-second-per-cycle run time than LSTM, as calculated.

Future research can be to real-time streams, geography, discipline, and reinforcement learning, improve more clustering with GMMs or Bayesian models, and improve more sentiment modelling with BERT. Incorporating the tools of scalability and explainability will guarantee compliance, transparency and applicability all around the world.

Funding source

None.

Conflict of Interest

The authors declare no potential conflict of interest in this publication.

References

- [1] Kumar, L., Khedlekar, S., & Khedlekar, U. K. (2024). A comparative assessment of holt winter exponential smoothing and autoregressive integrated moving average for inventory optimization in supply chains. *Supply Chain Analytics*, 8, 100084. <https://doi.org/10.1016/j.sca.2024.100084>
- [2] Shandilya, S. K., Datta, A., Kartik, Y., & Nagar, A. (2024). Role of artificial intelligence and machine learning. In *Digital Resilience: Navigating Disruption and Safeguarding Data Privacy* (pp. 313-399). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-53290-0_6
- [3] Fang, B., & Zhang, P. (2016). Big data in finance. In *Big data concepts, theories, and applications* (pp. 391-412). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-27763-9_11

- [4] Chowdhury, A. G., Deora, R., Prathikantam, R., & Kumar, S. (2025, March). Dynamic Clustering with Deep Learning for Customer Segmentation. In *2025 7th International Conference on Intelligent Sustainable Systems (ICISS)* (pp. 674-680). IEEE. <https://doi.org/10.1109/ICISS63372.2025.11076506>
- [5] Dritsas, E., & Trigka, M. (2025). Machine Learning in e-Commerce: Trends, Applications, and Future Challenges. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2025.3572865>
- [6] Ankita Ghosh, Sudip Diyasi, & Siddhartha Chatterjee. (2024). Enhancing SQL Injection Prevention: Advanced Machine Learning and LSTM-Based Techniques. *International Journal on Computational Modelling Applications*, 1(1), 20–31. <https://doi.org/10.63503/j.ijcma.2024.16>
- [7] Sharma, S. R., Singh, B., & Kaur, M. (2023). A novel approach of ensemble methods using the stacked generalization for high-dimensional datasets. *IETE journal of research*, 69(10), 6802-6817. <https://doi.org/10.1080/03772063.2022.2028582>
- [8] Dahish, Z., Miah, S. J., Pandit, A., & Roy, S. K. (2025). Enhancing phygital customer experience through generative AI: a social listening method for strategic retail decision-making. *Journal of Strategic Marketing*, 1-21. <https://doi.org/10.1080/0965254X.2025.2540267>
- [9] Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, 7(2), 139-172. <https://doi.org/10.1080/23270012.2020.1756939>
- [10] Sykora, M., Elayan, S., Hodgkinson, I. R., Jackson, T. W., & West, A. (2022). The power of emotions: Leveraging user generated content for customer experience management. *Journal of Business Research*, 144, 997-1006. <https://doi.org/10.1016/j.jbusres.2022.02.048>
- [11] Peltoniemi, M. (2015). Cultural industries: Product–market characteristics, management challenges and industry dynamics. *International journal of management reviews*, 17(1), 41-68. <https://doi.org/10.1111/ijmr.12036>
- [12] Bolón-Canedo, V., Sánchez-Marroño, N., & Alonso-Betanzos, A. (2016). Feature selection for high-dimensional data. *Progress in Artificial Intelligence*, 5(2), 65-75. <https://doi.org/10.1007/s13748-015-0080-y>
- [13] Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior*, 98, 277-284. <https://doi.org/10.1016/j.chb.2019.04.019>
- [14] Barikzai, S., Bharathi S, V., & Perdana, A. (2024). Challenges and strategies in e-learning adoption in emerging economies: a scoping review. *Cogent Education*, 11(1), 2400415. <https://doi.org/10.1080/2331186X.2024.2400415>
- [15] Jin, Y. C., Cao, Q., Wang, K. N., Zhou, Y., Cao, Y. P., & Wang, X. Y. (2023). Prediction of COVID-19 data using improved ARIMA-LSTM hybrid forecast models. *IEEE Access*, 11, 67956-67967. <https://doi.org/10.1109/ACCESS.2023.3291999>
- [16] Liu, B., & Lai, M. (2025). Advanced machine learning for financial markets: A PCA-GRU-LSTM approach. *Journal of the Knowledge Economy*, 16(1), 3140-3174. <https://doi.org/10.1007/s13132-024-02108-3>
- [17] Day, M. Y., Yang, C. Y., & Ni, Y. (2024). Portfolio dynamic trading strategies using deep reinforcement learning. *Soft Computing*, 28(15), 8715-8730. <https://doi.org/10.1007/s00500-023-08973-5>
- [18] Hwang, J., & Choi, L. (2020). Having fun while receiving rewards?: Exploration of gamification in loyalty programs for consumer loyalty. *Journal of business research*, 106, 365-376. <https://doi.org/10.1016/j.jbusres.2019.01.031>
- [19] Miraftabzadeh, S. M., Colombo, C. G., Longo, M., & Foiadelli, F. (2023). K-means and alternative clustering methods in modern power systems. *Ieee Access*, 11, 119596-119633. <https://doi.org/10.1109/ACCESS.2023.3327640>

- [20] Shan, S., Sun, J., & Macawile, R. M. C. (2025). Examining Customer Satisfaction Through Transformer-Based Sentiment Analysis for Improving Bilingual E-Commerce Experiences. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2025.3551666>
- [21] Bhati, B. S., Chugh, G., Al-Turjman, F., & Bhati, N. S. (2021). An improved ensemble based intrusion detection technique using XGBoost. *Transactions on emerging telecommunications technologies*, 32(6), e4076. <https://doi.org/10.1002/ett.4076>
- [22] Yao, J. (2024). A fusion method integrated econometrics and deep learning to improve the interpretability of prediction: evidence from Chinese carbon emissions forecast based on OLS-CNN model. *Computational economics*, 1-20. <https://doi.org/10.1007/s10614-024-10793-0>
- [23] Sert, M. F. (2025). A Hybrid ARIMA-LSTM/GRU Model for Forecasting Monthly Trends in Turkey's Gold and Currency Markets with a Macro-Economic Data-Driven Approach. In *Machine Learning in Finance: Trends, Developments and Business Practices in the Financial Sector* (pp. 35-51). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-83266-6_3
- [24] Anuj Kumar, & Ishika Arora. (2025). Development of an Advanced Traffic Demand Prediction System Optimized Three-Phase Deep Neural Network . *International Journal on Computational Modelling Applications*, 2(1), 28–41. <https://doi.org/10.63503/j.ijcma.2025.49>