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Adaptive Price Optimization: Leveraging Google Cloud AI for Real-Time Retail Transformation

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ABSTRACT

Dynamic pricing optimization is a groundbreaking strategy that enables businesses to enhance sales, improve customer experience and stay competitive in rapidly changing business environments. Conventional pricing strategies that employ static models and historical data frequently does not have the ability to vary instantaneously according to the action of pricing strategies, or customer behaviour. This research article presents an end-to-end solution utilizing cloud-based artificial intelligence with Google Cloud technologies such as Vertex AI, BigQuery, and Cloud Run, to carry out real-time pricing optimization. Various ensemble-based machine learning prediction models, like Random Forest, XGBoost ,LSTM and ARIMA time series models are used to predict prices and make real-time pricing predictions. This research article also highlights how the scalable, reliable, efficient and accurate system provide decision-makers with the capability to capture and incorporate observational data to establish reliable, data-driven pricing policies. Random Forest model performed best with the highest dynamic price prediction accuracy of 98.20% and mean absolute percentage error (MAPE) of 2.79while compared with other state of art methods like LSTM, xgboost and lightGBM because it can learn intricate temporal relationships in price data.

KEYWORDS: Dynamic Pricing, Cloud AI, Google Cloud, Vertex AI, BigQuery, Cloud Run, Real-Time Pricing, Machine learning, Time-Series Forecasting, Retail Optimization, Data Privacy, Ethical AI, Pricing Strategies, Random Forest, XGBoost, ARIMA, Prophet, LSTM.

I. INTRODUCTION

Pricing is a key consideration in today's retail strategy, impacting revenue, customer experience, and competitiveness. However, traditional pricing models that utilize a set of static rules and historical data will fail to respond dynamically to real-time market changes, competitor behaviour and customer purchasing behaviour. For example, the limitation of these traditional models can lead to poor pricing decisions, overlooked opportunities, and diminished competitiveness in a relatively fast-paced retail environment.

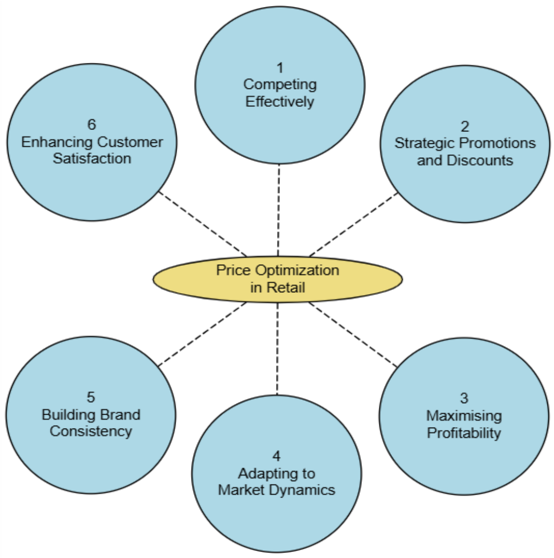

Fig 1: components involved in Price Optimization in Retail

Figure 1 represents Various components involved in the retail domain price optimization. However, with the advancements in cloud computing and artificial intelligence in supporting dynamic pricing, businesses can leverage the ability to continually optimize and recharge pricing in real time using changing consumer demand and other market conditions. By analysing historical data (i.e., sales and inventory history, competitors' pricing) and consumer demand patterns over time, businesses can make informed decisions about pricing and maximize revenue while considering the customer's satisfaction as key point by utilizing an unsupervised deep learning algorithms like ARIMA and Prophet. These enable effective demand forecasting and price predicting strategies and can introduce adaptation into pricing methodologies. By making cloud computing scalability and cost effectiveness, cutting edge AI and statistical modelling algorithms, this solution not only provides accurate result but also adaptable pricing models. Figure 2 gives the step-by-step procedure of workflow dynamic pricing in retail by using google cloud AI

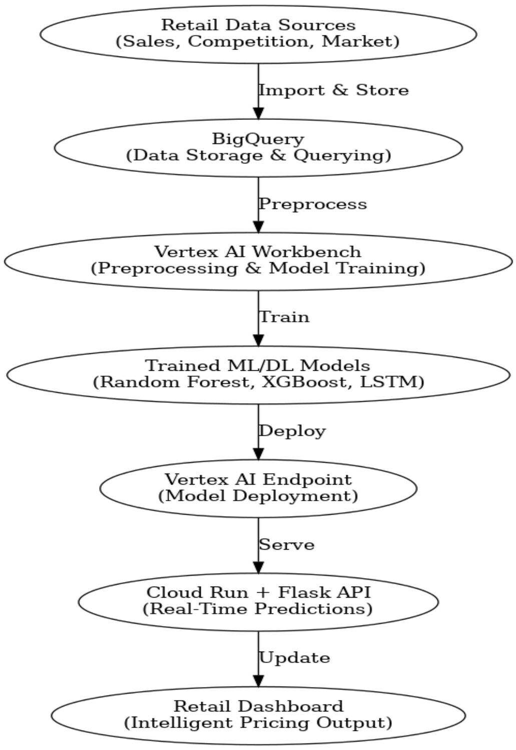

Fig 2. Workflow Dynamic pricing in retail powered by Google Cloud AI.

The rest of the article discusses related works in section II, detailed methodology in section III, results in section IV, future enhancements in section V ,Acknowledgement in section VI and conclusion in section VII.

II.RELATED WORKS

This section mainly concentrates on the discussion of various research works carried out in the field of dynamic pricing optimization, its current scenario complications, challenges and reshaping the artificial intelligence-based decision making in dynamic pricing optimizations.

Murat Basal et al [1] discussed about strategies of dynamic pricing using various artificial intelligence algorithms. He clearly mentioned the advantages and limitations of using different artificial intelligence algorithms in the area of dynamic pricing strategies.

Shubhy Gupta [2] explained clearly about Advanced AI-Driven Dynamic Pricing Models in real marketing and their applications. He focused mainly on reinforcement, machine learning models and neural networks strive towards US market and also design the system in such a way that businesses to adjust prices in real-time based on factors like demand, competition and customer behaviour. Key factors like price elasticity, revenue functions and optimization techniques are considered. Main challenges such as data privacy, computational complexity and various ethical issues also discussed.

Abid Haleem et al [3] reviewed several research works related to marketing using artificial intelligence. They also highlighted the potential of artificial intelligence in improving the data management capabilities especially when personalizing based on users' point of view. Radoslaw Wolniak et al [4] reviewed the impact of various key technologies like artificial intelligence, augmented reality etc. in grocery instore shopping on context of digital transformation. The major challenges in the integration of artificial intelligence with the traditional method are high implementation cost and also bias in different artificial intelligence algorithms.

This article [5] mainly focusses on the key role of AI cantered personalization and its major contribution on analysing market trends based on the intersection of behaviour of consumer and e-commerce. It mainly targets on customer satisfaction, improvement of customer engaging, loyalty etc. It also highlights futuristic market trends channelized by artificial intelligence through different aspects such as predictive analytics, optimizing management of inventory, proper virtual assistants like chatbots etc.

L Chen et al. [6] proposed a dynamic pricing model that included a mix of fixed (or flat) and floating prices, to reduce retailer risk from the day-ahead markets. The simulation results showed the potential to benefit both retailers and residents. For the residents, it encouraged them to shift energy consumption away from peak pricing windows; for the retailers, it optimized demand response through various fixed and floating pricing.

G Yamuna et al [7] discussed price optimization for online retail using machine learning techniques. Key takeaway from this research work is customer satisfaction, revamping the e-commerce profitability ensuring the further customization in the future, applying the concept of dynamic pricing models across wide range of variety of businesses. This article [8] mainly focusses on dynamic pricing models using machine learning methodologies in e-commerce industries. Marcin Nowak and Marta analysed different machine learning algorithms like decision trees, k-nearest neighbor, naive bayes classifier, support vector machine and the experiment result indicate that linear support vector machine provides promising result in prediction of pricing decisions [15].

Huaming Song and Yiken Chen [9] explored the impact of online reviews on the new products in the context of dynamic pricing. They also highlighted that skimming pricing strategy is suitable for low-cost firms and penetration pricing strategy best suits for high cost companies [14]. Research article also analysed the strategy of preferring low information and vague reviews for firms with high quality products and reviews with detailed and accurate information for low quality product firms.

K Aishwarya [10] worked in AI based dynamic pricing strategies for optimizing real time prices since it directly relates to the success of the business. AI plays a key role in the decision making of pricing strategies of products that enables it to stand tall among the competitive products in the e-commerce. The critical challenges like strategies for pricing, data privacy, transparency, ethics in pricing etc are taken into consideration. Robert Philips [11] worked on the price optimization for credit of consumer. But due to mispricing, consumer credit misallocation can create severe consequences in the global economy. Youjiang Gao and Hongfei Liu [12] discussed the customer perspective towards AI based personalization in a marketing that is exclusively interactive. This article mainly focuses on the contradictions in the personalization practices and also discussed the managerial point of approach to address such complications [13].

III. METHODOLOGY

Dynamic pricing has received considerable attention from researchers across various domains who have implemented machine learning and cloud technologies. Traditional statistical models such as ARIMA have performed well at forecasting linear trends but have struggled with more complex non-linear data from retail. Machine learning models such as Random Forest and XGBoost have been appropriate in providing better accuracy on demand for pricing. Demand prediction has been an area of study and research has shown hybrid models or combinations of ARIMA and LSTM to handle linear and non-linear dependencies found in large datasets. Most related works also discussed the scalability and cost-effectiveness of deploying real-time pricing in the major cloud vendors such as Google Cloud, AWS and Azure. Further challenges of data privacy, fairness and interpretability of AI models has been the most discussed challenges in dynamic pricing with solutions focused on ethical AI practices and compliance with regulation. This paper builds off these challenges by using Google Cloud services and current AI technology to expand on everyday pricing challenges in retail.

A. Data Acquisition

To develop an effective dynamic pricing strategy, the first step is to acquire heterogeneous data from different sources, such as historical sales data, competitive pricing data, and external market factors as shown in figure 3.

The historical sales data, competitive pricing data and external market conditions are the basis for a dynamic pricing model. Historical sales data consists of transaction details of sales (by category), including marketing and discounting promotional activity, as well as the demographic profiles of customers. Historical sales are the foundation of understanding the demand curve over time. In parallel, competitive pricing data - collected in real time, either through web scraping or through APIs from a competitors' website - tells the story of market pricing thus ensuring the ability for the business to react quickly to a market shift to ensure they remain competitive. External market conditions, such as seasonal behaviour, holiday cycles, macro-economic factors (inflation rates, consumer spending activity), can all impact pricing decisions too. When all these different data sources are brought into the model, it will provide an accurate framework for pricing, while still creating a fluid model capable of responding quickly to changes in the market. .

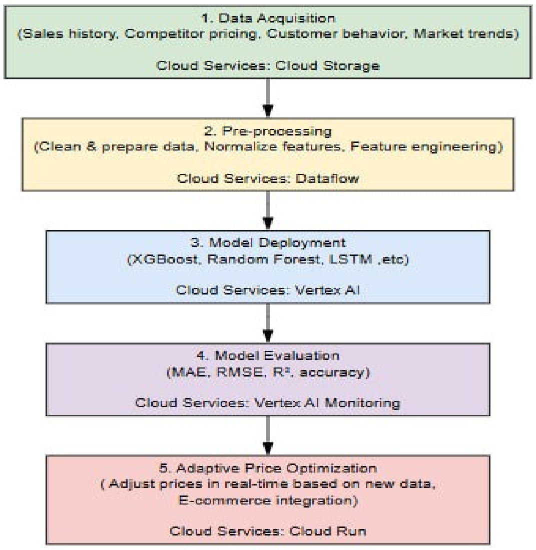

Fig.3: End-to-End Workflow of Dynamic Pricing Optimization using Google Cloud Services.

B. Preprocessing

Data pre-processing can be effectively accomplished on Google Cloud using BigQuery services, where Python scripts are executed within the Vertex AI Workbench to ensure efficiency and scalability. Two main steps are involved in the data pre-processing process:

- Data Cleaning
- Data Normalization
- Feature Engineering

Data cleaning and normalizing ultimately happen to guarantee the quality and validity of the dataset before model development. Outliers are eliminated carefully, and missing values are imputed where needed to comply with the data completeness. The dataset is cleaned and the data in it has been passed through normalization to enforce a standard scale in the data to ensure uniformity of data points across the board and to make sure no single feature is dominating an models predictions based on their scale in the dataset with the other features. After cleaning and normalizing then parameter engineering occurs to build new features such as, moving averages, demand seasonality or price elasticity where they can be used in the further prediction steps to assist in model performance and accuracy.

C. Model Development

This phase mainly focuses on a rigid and scalable pricing framework, which predicts optimal prices based on historical data, competitor price and other external factors. It is broadly categorized into the following two methods:

- Time Series Models
- Machine Learning Models

Various time series models like **ARIMA** (Auto Regressive Integrated Moving Average), **SARIMA** (Seasonal ARIMA), and **Prophet** are widely used for pricing and forecasting purposes. On the other hand, machine learning models are also widely used because of their improved accuracy in prediction. In the proposed architecture, the **Random Forest** model is used for price prediction and its performance is compared with other state-of-the-art methods like **XGBoost**, **LightGBM**, and **LSTM** models. because it reduces overfitting by averaging together multiple decision trees and better captures complex, non-linear relationships. Random Forest uses its ensemble principle to make better predictions which are strong and stable despite noisy data or high-dimensional data.

D. Model Evaluation

Models were evaluated with the following metrics are used to assess accuracy and reliability of the proposed methodology:

1.Mean Absolute Error (MAE): This is a means of measuring the average magnitude of errors in predicted values. This is a direct, absolute measure of how well a model is performing.

$$\boldsymbol{MAE = \frac{1}{n}\sum_{i=1}^{n} |\, x_i - x|}$$

2.Root Mean Squared Error (RMSE): This captures the standard deviation of the prediction errors, and as a result, penalizes large deviations more than MAE. This would be useful in determining or comparing models that consistently perform well.

$$\boldsymbol{RMSE = \sqrt{\frac{I}{n}\sum_{i=1}^{n}(x_i - x)^2}}$$

3.Mean Absolute Percentage Error (MAPE): This expresses the errors of the predictions as a percentage of actual value, and therefore this could be the best metric for comparing models applied to different datasets (different scales).

$$\boldsymbol{MAPE = \frac{100}{n}\sum_{i=1}^{n} |\frac{x_i - x}{x_i}|}$$

4.Accuracy: The percent of correct predictions to a specified tolerance; would be useful for pricing decisions made with classification.

$$\boldsymbol{Accuracy} = \left(\mathbf{1} - \frac{\boldsymbol{MAE}}{\boldsymbol{Mean\ of\ Actual\ Values}}\right) \times \mathbf{100}$$

E. Cloud Deployment and Interactive Visualization

By deploying the predictive model in a cloud environment, we allow the application to scale, be accessible, and process dynamically in benefit of the dynamic pricing optimization. The Google Cloud Platform (GCP) will be the core of the cloud hosting our system, which has services like Vertex AI, BigQuery and Cloud Run. The trained model will be hosted through Google Cloud Vertex AI, which provides infrastructure with real-time API hosting capabilities. The model will be exported into a format, uploaded as deployable model in Vertex AI. Endpoints will be created to enable real-time interaction on vertex AI incoming data will be received, processed and return optimized pricing suggestions. APIs built with Flask will be packaged with Docker, then deployed into the Cloud Run environment to achieve scalability and reliability. The model deployment also supports horizontal scaling for increased data, volume and traffic processing without disruption for users during peak times.

IV. RESULTS AND DISCUSSION

The dataset for this project was taken from Kaggle, titled "Market Sales Dataset." that includes historical sales data that would be helpful for price optimization and predictive modelling tasks.

Figure 4 demonstrates the Dataset is being uploaded to the Cloud Storage of google cloud. Cloud Storage bucket named as "dynamic-pricing-dataset" was created to store the dataset in a secure and reliable manner. The above-mentioned dataset was uploaded, allowing us to subsequently carry out additional courses of action in BigQuery and Vertex AI.

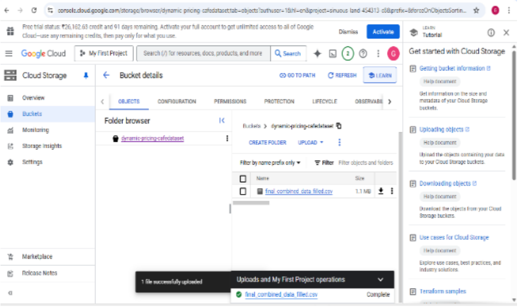

Fig 4: Cloud Storage Bucket named "dynamic-pricing-dataset" with the uploaded dataset.

Store and Query Data in BigQuery: Google BigQuery is a fully managed, serverless and highly scalable data warehouse that is meant to enable fast SQL-based analysis of large datasets. Once the dataset was uploaded to Cloud Storage, it was imported into BigQuery to enable easy data querying, preprocessing and transformation directly in the cloud.it allows the user to evaluate large datasets with minimal operational burden and was an excellent choice to prepare the sales data for model training and model evaluation in Vertex AI.

In figure 5, BigQuery, the uploaded data was stored in a dataset called "pricing data." A table, "pricing table" was created within that dataset for convenient and effective querying and analysis of historical sales, your competitors' pricing, and market components.

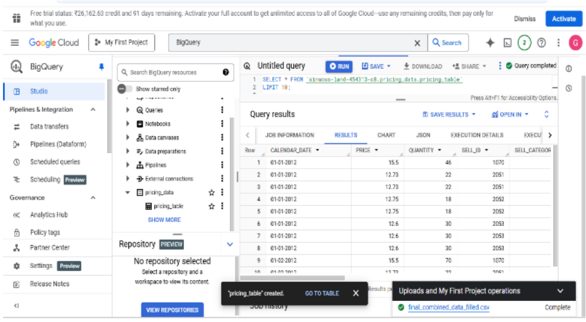

Fig. 5: BigQuery Dataset "pricing_data" with Table "pricing_table".

Train a Model in Vertex AI: The training dataset was created and used the use of BigQuery while being imported into Vertex AI in preparation for the model. "Pricing data" as the dataset name and "pricing data" as the dataset table were sourced from BigQuery and imported into Vertex AI as shown in figure 6. Using the Vertex AI platform, a new dataset was created by selecting Tabular Data as a dataset type and choosing BigQuery table as the source, ensuring smooth data flow for training purposes.

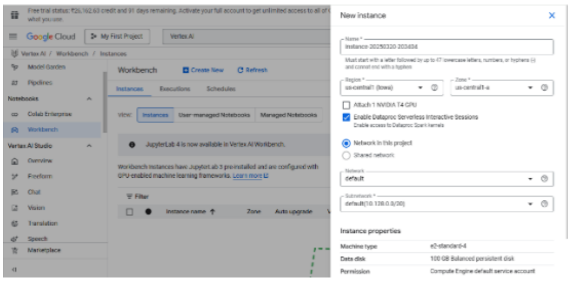

Fig 6: Vertex AI Workbench Instance

To prepare and train the data, a free-tier Vertex AI Workbench instance was used. This instance was set up with Python 3 for data loading and processing. Once the Jupyter Notebook was started in the Workbench, a couple of libraries were installed, and loaded to BigQuery for preprocessing. The preprocessing involved taking care of missing values, scaling numerical data, and engineering features such as moving averages, seasonality, and price elasticity as shown in figure 7.

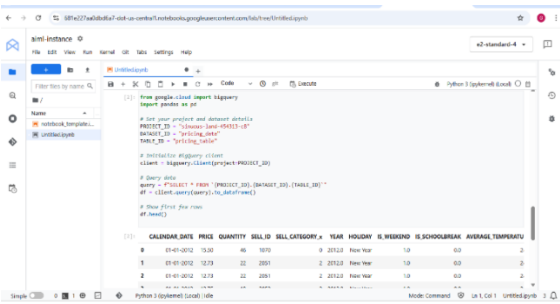

Fig 7: Vertex AI Workbench Setup and Data Pre-processing

Overview: The data was used to train different models for the predictions of dynamic pricing. Time-series models (ARIMA, SARIMA, and Prophet) were used to represent the seasonal and temporal characteristics of the data. Machine learning models were used to capture the non-linear relationships and complex patterns in our data (Random Forest, XGBoost, and LightGBM) along with LSTM deep learning models. As shown in table 1 These models were assessed using standard metrics which resulted in:

```
           Model       MAE      RMSE      MAPE   Accuracy
0  Random Forest  0.342773  0.468926  2.797083  97.202917
1        XGBoost  0.344286  0.458262  2.813448  97.186552
2       LightGBM  0.353524  0.462471  2.885742  97.114258
3           LSTM  0.724005  0.737829  5.817740  94.182260

Best Model:
Model       Random Forest
MAE              0.342773
RMSE             0.468926
MAPE             2.797083
Accuracy        97.202917
Name: 0, dtype: object
```

Fig 8: Performance Metrics of Time-Series and Machine Learning Models for Dynamic Pricing Predictions

Model	MAE	RMSE	MAPE	Accuracy
Random Forest	0.345	0.468	2.797	97.202
XG Boost	0.344	0.458	2.814	97.186
Light BGM	0.353	0.464	2.885	97.114
LSTM	0.724	0.737	5.817	94.182

Table 1: Performance Comparison of Machine Learning Models for Price Prediction

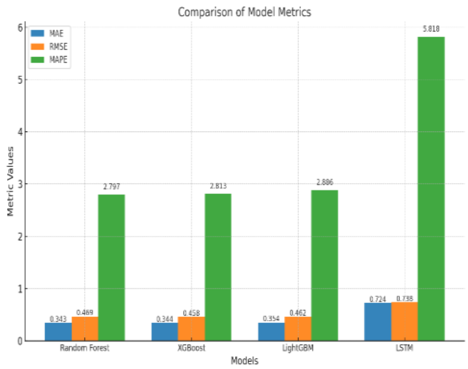

Fig 9: Comparison of MAE, RMSE, and MAPE Metrics for Different Models

Figures 8 and 9 illustrates the comparison of machine learning models for price prediction.

V.FUTURE ENHANCEMENTS

Future work may include the integration of reinforcement learning for adaptive pricing, incorporation of real-time data sources about customer sentiments or social media trends to drive analytics, and utilization of explainable A.I. to improve the interpretability of models. Addition of multi-cloud support, integration of IoT for in-store data, and ethical AI practices will also upgrade the system performance. Allowing for multi-language dashboards would improve access for global customers, while enhanced estimation of demand elasticity would improve precision in pricing recommendations across geo-regions. Leveraging automated pipeline retraining will also help maintain the system over time by fully adapting to market changes as they occur.

VI. ACKNOWLEDGEMENT

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VII.CONCLUSION

This research article discussed the proposed dynamic pricing system model which provides accurate, reliable and scalable pricing recommendations. The system compared with state of art methods like XGBoost, LightGBM, Random forest and LSTM. provides significant results in terms of low MAE, RMSE and MAPE. provides significant results in terms of low MAE, RMSE and MAPE. states that the ability to deal with complex, real world retail scenarios. They advantage is Cloud deployment, utilizing Vertex AI and BigQuery services, data integration, real-time scale, easy access and interactive dashboards provides insights that stakeholders can easily put into action. This system can adapt to both dynamic market changes and seasonal variations providing a viable solution for a contemporary retail context. With suitable enhancements such as reinforcement learning, IoT integration, and explainable AI, the system stands further to the dynamic changes in retail pricing, encouraging competitiveness, customer satisfaction, and recurring revenue stream growth.

REFERENCES

[1] M. Basal, E. Saraç, and K. Özer, “Dynamic pricing strategies using artificial intelligence algorithms,” Journal of Revenue and Pricing Management, vol. 24, no. 1, pp. 45–62, 2025.

[2] S. Gupta, “AI-driven dynamic pricing models in marketing,” Marketing Science, vol. 44, no. 3, pp. 567–583, 2025.

[3] Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. International Journal of Intelligent Networks, 3, 119-132.

[4] Wolniak, R., Stecuła, K., & Aydın, B. (2024). Digital transformation of grocery In-store shopping-scanners, artificial intelligence, augmented reality and beyond: A review. Foods, 13(18), 2948.

[5] M. A. Raji et al., "E-commerce and consumer behavior: A review of AI-powered personalization and market trends," GSC Adv. Res. Rev., vol. 18, no. 3, pp. 66-77, 2024.

[6] Chen, L., Yang, Y., & Xu, Q. (2021). Retail dynamic pricing strategy design considering the fluctuations in day-ahead market using integrated demand response. International Journal of Electrical Power & Energy Systems, 130, 106983.

[7] Yamuna, G., Dhinakaran, D. P., Vijai, C., Kingsly, P. J., & Devi, S. R. (2024, April). Machine Learning-Based Price Optimization for Dynamic Pricing on Online Retail. In 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 1-5). IEEE.

[8] Nowak, M., & Pawłowska-Nowak, M. (2024). Dynamic Pricing Method in the E-Commerce Industry Using Machine Learning. Applied Sciences (2076-3417), 14(24).

[9] A. Immadisetty, "Dynamic pricing strategies in retail: Leveraging real-time data analytics for competitive advantage," J. Recent Trends Comput. Sci. Eng., vol. 13, no. 1, pp. 53-65, 2025.

[10] K. A. Pillai, "AI-driven dynamic pricing strategies for subscription features: Leveraging artificial intelligence for real-time pricing optimization," Cem Dilmegani, 2023.

[11] Phillips, R. (2013). Optimizing prices for consumer credit. Journal of Revenue and Pricing Management, 12, 360-377.

[12] Y. Gao and H. Liu, "Artificial intelligence-enabled personalization in interactive marketing: A customer journey perspective," J. Res. Interact. Mark., vol. 17, no. 5, pp. 663-680, 2023.

[13] M. Awais, "Optimizing dynamic pricing through AI-powersed real-time analytics: The influence of customer behavior and market competition," Qlantic J. Social Sci., vol. 5, no. 3, pp. 99-108, 2024.

[14] Jawabri, A., Mohamed, A., & Rehman, W. U. (2025). The Impact of Artificial Intelligence on eCommerce in the UAE from the Customer Perspective. innovation, 15(1).

[15] Reddy, V. M., & Nalla, L. N. (2024). Personalization in E-Commerce Marketing: Leveraging Big Data for Tailored Consumer Engagement. Revista de Inteligencia Artificial en Medicina, 15, 691-725.