

Machine Learning-Based Dynamic Pricing and Customer Retention Among E-Commerce Businesses in Akwa Ibom State, Nigeria

Uduak-Obong Ekpo-Ufot^{1*}, Umoh Oku Sunday¹, Udo Agnes Umana¹

¹ Department of Business Management, Faculty of Management Sciences, University of Uyo, Akwa Ibom State, Nigeria

*Corresponding author

Key Words

Machine Learning-Based
Dynamic Pricing, Customer
Retention, E-commerce
Businesses

DOI:

10.59413/amsj/v1.i1.9

Published on:

7th October 2026

Abstract

The rapid digitalisation of commerce has made customer retention a critical success factor for e-commerce businesses. This study examines the relationship between machine learning-based dynamic pricing and customer retention among e-commerce firms in Akwa Ibom State, Nigeria. A survey research design was adopted to collect quantitative data from a representative sample of e-commerce businesses. Regression analysis was employed to test the hypothesis that machine learning-driven dynamic pricing positively influences customer retention. The findings revealed a strong positive correlation ($R = 0.728$) and indicated that machine learning-based dynamic pricing accounts for 53.0% of the variance in customer retention ($R^2 = 0.530$). The regression model was statistically significant ($F = 436.864$, $p < 0.05$), with a positive coefficient ($\beta = 0.700$, $p < 0.001$), confirming that real-time, personalised pricing significantly enhances customer loyalty. The study concludes that adopting machine learning for dynamic pricing is a strategic tool for improving customer retention by offering competitive, fair, and market-responsive prices. It is recommended that e-commerce firms invest in AI-driven pricing technologies and that policymakers support digital adoption to strengthen business competitiveness.

1. INTRODUCTION

The digital economy has profoundly transformed retail commerce, with e-commerce emerging as a dominant force in global and regional markets. In Africa, e-commerce revenues have surged significantly, with Nigeria's Business-to-Consumer (B2C) index reaching 53.2 points and a 55% internet penetration rate recorded in 2023, ranking fourth highest on the continent (Abdulsalam et al., 2024). Akwa Ibom State has actively positioned itself within this digital transformation, as evidenced by the recent launch of Easy Pay Shop, a homegrown e-commerce platform designed to boost Micro, Small and Medium Enterprises (MSMEs), create jobs, and promote Made-in-Akwa-Ibom products (Akwa Ibom Unveils Easy Pay Shop, 2025). The platform, supported by the Ministry of Trade and Investment and the Ministry of Youth Development, aims to expand market access, increase productivity, and drive sustainable private-sector-led growth. Pricing strategy constitutes one of the four pillars of the traditional marketing mix and remains a critical determinant of business performance in the e-commerce sector. In the dynamic and competitive environment of e-commerce, pricing is extremely important in maintaining profitability and customer satisfaction. Traditional static pricing models and generic customer engagement strategies are no longer sufficient in a market driven by personalized experiences and real-time decision-making. Unlike conventional retail environments, digital marketplaces exist in highly dynamic conditions where consumer preferences, competitor prices, and demand patterns may vary within minutes (Ye et al., 2023). Consequently, fixed pricing policies are becoming less effective in modelling short-term demand changes and reacting to market indicators.

The introduction of machine learning (ML) into dynamic pricing has brought price optimisation to new standards of accuracy, effectiveness, and dynamism. With machine learning-enabled dynamic pricing systems, e-commerce and retail businesses can optimise prices in real-time based on consumer behaviour, demand patterns, and market trends (Machine Learning-driven Dynamic Pricing Strategies in E-Commerce, 2023). Machine learning models can predict ideal price levels and manage trade-offs between revenue maximisation and customer retention while reacting to changes in market conditions (Using Machine Learning for Dynamic Pricing Strategies in Retail and Online Markets, 2026). Empirical evidence demonstrates that ML-driven dynamic pricing systems produce high levels of enhancement in pricing accuracy, revenue increment, and customer retention (Machine Learning-Driven Dynamic Pricing System for E-Commerce Revenue Optimization, 2026). The nexus between dynamic pricing and customer retention has attracted significant scholarly attention. Customer churn remains a significant issue across industries such as e-commerce, telecom, and subscription-based services, often leading to substantial revenue loss and reduced customer loyalty (Ahn et al., 2020). AI-powered pricing strategies have been shown to help businesses deal with changes in the market and keep customers coming back by adjusting prices based on demand and customer characteristics (Chukwuemeka, 2023). Research has demonstrated that strategic application of dynamic pricing not only reduces customer churn but also increases overall revenue through enhanced purchase volume (Khazaei et al., 2024). Furthermore, AI-powered solutions can estimate customer attrition, automate pricing techniques, and ultimately enhance customer satisfaction and retention rates (Zeinali et al., 2026). Despite the growing body of literature on ML-based dynamic pricing globally, there remains a paucity of empirical research examining this phenomenon within the Nigerian e-commerce context, particularly in sub-Saharan African digital marketplaces characterised by unique economic volatilities, currency fluctuations, and consumer trust challenges. This study, therefore, seeks to investigate the relationship between machine learning-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State, Nigeria.

1.1. Statement of the Problem

E-commerce businesses in Akwa Ibom State operate within a challenging economic environment marked by fluctuating currency values, rising logistics costs, and intense competition in the digital marketplace. Many online retailers in Nigeria struggle with customer retention despite the potential for growth in the sector. Traditional manual pricing approaches leave businesses perpetually one step behind competitors, with price discrepancies resulting in lost customers and eroded profit margins. The globalisation of markets has exposed e-commerce companies to economic downturns, compelling them to adopt strategic pricing approaches to ensure sustained profitability and competitiveness. Consumers have become more price-sensitive, emphasising the need for firms to accurately gauge pricing sensitivity to influence purchasing decisions effectively (Abdulsalam et al., 2024). In the Nigerian e-commerce context, one of the biggest hurdles is consumer trust—customers are often wary of sudden price jumps, making transparent and data-backed pricing essential for customer retention. While machine learning-based dynamic pricing has demonstrated significant potential for optimising revenue and enhancing customer retention in developed markets (Li & Chen, 2025; Ma, 2025; Sun et al., 2024), there is limited empirical evidence on its application and effectiveness in the Nigerian e-commerce sector. The challenge facing e-commerce businesses in Akwa Ibom State is twofold: first, the absence of systematic, data-driven pricing frameworks that can respond to real-time market dynamics; and second, the lack of empirical understanding of how ML-based dynamic pricing influences customer retention in this specific context. This study addresses this gap by investigating the relationship between ML-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State.

1.2. Objective of the Study

The main objective of this study is to examine the relationship between machine learning-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State, Nigeria.

1.3. Research Question

What is the relationship between machine learning-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State, Nigeria?

1.4. Hypothesis

There is no significant relationship between machine learning-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State, Nigeria.

2. REVIEW OF RELATED LITERATURE

2.1. Machine Learning-Based Dynamic Pricing

Machine learning-based dynamic pricing refers to the use of artificial intelligence algorithms to adjust product prices in real-time based on consumer behaviour, demand patterns, market trends, and competitive data. This approach has evolved from simple rule-based systems to more powerful AI-driven systems that offer tailored pricing strategies (Machine Learning-driven Dynamic Pricing Strategies in E-Commerce, 2023). Machine learning methods such as Naive Bayes classifiers, support vector machines (linear and nonlinear), decision trees, and k-nearest neighbour algorithms have been applied to classify pricing decisions in e-commerce. Empirical results indicate that linear support vector machines can achieve accuracy rates as high as 86.92% in classifying pricing decisions (Dynamic Pricing Method in the E-Commerce Industry Using Machine Learning, 2024). Dynamic pricing seeks to find optimal prices using elasticity of demand, inventory levels, time effects, and customer behaviour (Fraija et al., 2024). The integration of reinforcement learning methods, particularly Deep Q-Network (DQN) agents, has demonstrated higher predictive accuracy and more stable pricing behaviour, with R-squared values reaching 98.74 (Sun et al., 2024). Hybrid models combining deep learning and reinforcement learning have further enhanced real-time dynamic pricing capabilities with demand-aware optimisation (Hybrid Machine Learning and Deep Reinforcement Learning for Real-Time Dynamic Pricing in E-Commerce with Demand-Aware Optimization, 2026). Reinforcement learning-based dynamic pricing systems have been shown to adapt to dynamic market conditions with greater flexibility than traditional methods such as XGBoost, multiple linear regression, and decision trees (Ardjmand et al., 2025). Studies have also demonstrated that the integration of price elasticity information with RL agents further enhances accuracy and minimises price deviation (Nomura et al., 2025). Furthermore, deep reinforcement learning approaches incorporating fairness constraints have been developed for discriminatory pricing models, ensuring ethical considerations in pricing decisions (Wang et al., 2025).

Customer Retention

Customer retention refers to the ability of a business to retain its existing customers over time, preventing them from switching to competitors. Customer churn—the loss of customers—remains a significant issue across industries including e-commerce, often leading to substantial revenue loss and reduced customer loyalty (Ahn et al., 2020). In the e-commerce context, customer retention is critical for sustaining growth and profitability. Machine learning models for customer churn prediction have become increasingly sophisticated. Transformer-based models, hybrid frameworks combining deep learning and boosting, graph-based attention mechanisms, and statistical survival analysis have all been shown to improve prediction accuracy (Zeinali et al., 2026). Ensemble approaches such as XGBoost and Random Forest have demonstrated superior performance compared to classical classifiers in forecasting churn (Khazaei et al., 2024). By analysing historical data and employing models such as logistic regression, Random Forest, and XGBoost, businesses can forecast churn risks and implement proactive retention strategies (Machine Learning Based Churn Analysis for Sellers on the E-Commerce Marketplace, 2023). Research has shown that combining machine learning methods with fuzzy logic produces effective predictions of customer attrition in electronic commerce (Zeinali et al., 2026). Strategic discount application using RFM (Recency, Frequency, Monetary) customer segmentation with machine learning methods has been shown to reduce customer churn and increase overall revenue (Chukwuemeka, 2023). Studies have demonstrated that Random Forest methods are superior to other ML methods in both churn and price predictions, achieving predictive accuracy of 94% and AUC of 98% (Joy et al., 2024).

E-commerce in Akwa Ibom State

Akwa Ibom State has emerged as a growing hub for digital commerce in Nigeria. The launch of Easy Pay Shop, a homegrown e-commerce platform designed to boost MSMEs and promote Made-in-Akwa-Ibom products, represents a significant step towards expanding the state's digital economy (Akwa Ibom Unveils Easy Pay Shop, 2025). The platform is described as a secure and scalable digital marketplace aimed at positioning Akwa Ibom as a hub for technology-driven trade in Nigeria. It enables local businesses to reach wider state and national markets while reducing barriers to e-commerce participation. Additionally, there are 15 live Shopify stores operating in Akwa Ibom State, indicating a growing presence of e-commerce activities in the state (Shopify Stores in Akwa Ibom, Nigeria, 2026). The growth of e-commerce in Akwa Ibom State must be understood within the broader context of the state's business environment. Studies have examined various factors influencing business operations in the state. For instance, Abaikpa, Thomas, and Udoh (2024) examined the relationship between human capital management and organizational performance in United Bank for Africa Plc, Uyo, Akwa Ibom State, finding a positive significant relationship between human capital management and organizational performance, with organizational performance dependent on the extent of staff training and timely appraisal of employees. Similarly, Abaikpa, Thomas, Udoh, and Udom (2024) investigated the relationship between emotional intelligence and organizational performance in commercial banks in Uyo Metropolis, revealing a significant and positive relationship between emotional intelligence variables such as self-control and self-management and employee performance. These findings underscore the importance of human capital development for business success in Akwa Ibom State—a principle equally applicable to e-commerce enterprises seeking to leverage technology for competitive advantage.

Furthermore, Abaikpa, Brownson, Enang, and Kumbur (2026) examined the effect of cashless policies on operations of market women in Akpan Andem Market, Uyo, Akwa Ibom State. The study provides important context for understanding the digital transformation of commerce in the state, as cashless policies have driven the adoption of digital payment systems that are fundamental to e-commerce operations. The findings highlight both the opportunities and challenges faced by businesses in adapting to digital financial systems—a dynamic that directly impacts e-commerce pricing and customer retention strategies. Thomas, Abaikpa, Daniel, and Akpan (2024) conducted a study on the imperatives of small-scale businesses and employment generation in Uyo Local Government Area, Akwa Ibom State. Their research revealed a positive relationship between small-scale businesses and employment generation, emphasising the crucial role that Small and Medium Enterprises (SMEs) play in the economy, providing employment and fostering innovation. This finding is particularly relevant to the present study, as many e-commerce businesses in Akwa Ibom State operate as SMEs, and their ability to retain customers through innovative pricing strategies directly affects their sustainability and employment generation capacity. Abaikpa (2025) examined the effect of performance management systems on small and medium enterprises in Uyo, Akwa Ibom State, Nigeria. The study provides empirical evidence on the factors that influence SME performance in the state, offering a foundation for understanding how management practices—including pricing strategies—affect business outcomes. The findings suggest that systematic management approaches are essential for SME success, reinforcing the argument that data-driven pricing frameworks such as ML-based dynamic pricing can enhance e-commerce business performance.

2.2. Theoretical Review

Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB), as applied in e-commerce pricing research, provides a framework for understanding how pricing strategies influence consumer purchasing decisions. TPB posits that behavioural intentions are shaped by attitudes toward the behaviour, subjective norms, and perceived behavioural control. In the context of dynamic pricing, consumers' price perceptions and their behavioural responses to price changes can be understood through this theoretical lens. Research applying PLS-SEM guided by TPB has demonstrated that various digital pricing strategies significantly impact consumer patronage and purchase satisfaction (Abdulsalam et al., 2024). The TPB framework has been effectively employed to examine how special event pricing, sample product pricing, and loss leader pricing significantly impact consumer patronage, while product lining pricing, captive pricing, and optional pricing strategies influence online purchase satisfaction (Abdulsalam et al., 2024). This theoretical foundation is particularly

relevant for understanding how ML-based dynamic pricing may influence customer retention through its effects on consumer perceptions and behavioural intentions.

Reinforcement Learning Theory

Reinforcement learning (RL) provides the theoretical foundation for many ML-based dynamic pricing systems. RL is a machine learning method that learns through customer actions, optimising decisions based on rewards and penalties (Fraija et al., 2024). In dynamic pricing applications, RL-based pricing agents such as Deep Q-Network (DQN) and Monte Carlo Tree Search (MCTS) agents learn optimal pricing policies through interaction with the market environment (Sun et al., 2024). The flexibility of RL-based agents to adapt to dynamic conditions has been shown to be superior to traditional methods such as XGBoost, multiple linear regression, and decision trees (Ardjmand et al., 2025). Research on deep reinforcement learning for dynamic pricing and ordering policies in perishable inventory management has demonstrated the effectiveness of RL approaches in complex decision-making environments (Nomura et al., 2025). Additionally, studies on two-stage deep reinforcement learning-driven dynamic discriminatory pricing models have incorporated fairness constraints, addressing the ethical dimensions of dynamic pricing (Wang et al., 2025). The integration of graph-embedded reinforcement learning for dynamic pricing has shown promise in capturing network effects and optimising pricing decisions in interconnected market environments (Ardjmand et al., 2025). Deep Q-learning optimisation frameworks for dynamic pricing in e-commerce have demonstrated superior performance in revenue optimisation compared to traditional approaches (Li & Chen, 2025). Deep reinforcement learning-driven dynamic pricing strategy optimisation for e-commerce platforms has further validated the theoretical underpinnings of RL in pricing applications (Ma, 2025).

2.3. Empirical Review

Machine Learning in Dynamic Pricing

Empirical studies have extensively examined the application of machine learning to dynamic pricing. A study on machine learning for dynamic pricing strategies in retail and online markets demonstrated how ML models can predict ideal price levels and manage trade-offs between revenue maximisation and customer retention while reacting to changes in market conditions (Using Machine Learning for Dynamic Pricing Strategies in Retail and Online Markets, 2026). The research highlighted practical implications including ethical considerations such as fairness, transparency, and consumer trust. A machine learning-driven dynamic pricing system for e-commerce revenue optimisation, utilising Bidirectional Long Short-Term Memory (BiLSTM) networks combined with attention mechanisms, demonstrated high levels of enhancement in pricing accuracy, revenue increment, and customer retention (Machine Learning-Driven Dynamic Pricing System for E-Commerce Revenue Optimization, 2026). The proposed system showed higher forecasting accuracy and lower error rates compared to traditional models. Research on hybrid machine learning and deep reinforcement learning for real-time dynamic pricing in e-commerce found that machine learning algorithms have gained massive application in predicting demand and purchase likelihood (Hybrid Machine Learning and Deep Reinforcement Learning for Real-Time Dynamic Pricing in E-Commerce with Demand-Aware Optimization, 2026). Supervised learning algorithms including logistic regression, support vector machines, and ensemble models showed high predictive accuracy in predicting customer buying behaviour.

Studies on dynamic pricing methods in the e-commerce industry using machine learning have demonstrated the effectiveness of various ML approaches in price optimisation (Dynamic Pricing Method in the E-Commerce Industry Using Machine Learning, 2024). Research on dynamic pricing models in e-commerce exploring machine learning techniques to balance profitability and customer satisfaction has provided insights into the trade-offs involved in pricing decisions (Dynamic Pricing Models in E-Commerce: Exploring Machine Learning Techniques to Balance Profitability and Customer Satisfaction, 2025). Additionally, studies on dynamic pricing optimisation in e-commerce using AI and machine learning have presented comprehensive frameworks for demand prediction and revenue maximisation (Dynamic Pricing Optimization in E-Commerce Using AI and Machine Learning: A Comprehensive Framework for Demand Prediction and Revenue Maximization, 2025). Empirical evidence has shown that deep Q-learning optimisation frameworks for

dynamic pricing in e-commerce can significantly enhance revenue performance (Li & Chen, 2025). Deep reinforcement learning-driven dynamic pricing strategy optimisation for e-commerce platforms has further demonstrated the effectiveness of advanced RL techniques in pricing applications (Ma, 2025). Research on dynamic pricing models for e-commerce products based on DDQN has shown that double deep Q-learning approaches can effectively balance exploration and exploitation in pricing decisions (Sun et al., 2024).

Machine Learning and Customer Retention

Empirical evidence on the relationship between ML-based pricing and customer retention is growing. A study presenting an AI-driven integrated system for churn prediction and dynamic pricing found that multiple approaches including transformer-based models, hybrid frameworks combining deep learning and boosting, and graph-based attention mechanisms have all been shown to improve prediction accuracy (Zeinali et al., 2026). Research on AI-powered dynamic pricing and customer retention systems for e-commerce platforms utilised reinforcement learning-based dynamic pricing engines that optimise product pricing within set ranges, combined with collaborative filtering-based recommender systems that personalise product suggestions (Chukwuemeka, 2023). This integration addresses the critical need for both dynamic pricing and personalised customer engagement in today's competitive e-commerce environment. An AI-driven personalised pricing approach for optimising customer retention demonstrated that Random Forest methods are superior to other ML methods in both churn and price predictions, achieving predictive accuracy of 94% and AUC of 98% (Joy et al., 2024). The proposed personalised pricing model could prevent churn and increase profitability by up to 36%. Studies on machine learning methods for customer churn prediction have shown that combining machine learning methods with fuzzy logic produces effective predictions of customer attrition in electronic commerce (Zeinali et al., 2026). Strategic discount application using RFM (Recency, Frequency, Monetary) customer segmentation with machine learning methods has been shown to reduce customer churn and increase overall revenue (Chukwuemeka, 2023). Research on machine learning based churn analysis for sellers on the e-commerce marketplace has demonstrated the importance of predictive analytics in identifying at-risk customers (Machine Learning Based Churn Analysis for Sellers on the E-Commerce Marketplace, 2023). Studies advancing machine learning frameworks for customer retention and propensity modelling in e-commerce platforms have provided valuable insights into predictive retention strategies (Chukwuemeka, 2023).

Digital Pricing in the Nigerian Context

Research on digital pricing strategies in the Nigerian e-commerce industry has demonstrated the significance of pricing on consumer behaviour. A study employing PLS-SEM guided by the Theory of Planned Behaviour found that special event pricing (0.433, 91.8% effect), sample product pricing (0.236, 85.0% effect), and loss leader pricing (0.236, 93% effect) significantly impact Gen Z consumer patronage (62.4%) (Abdulsalam et al., 2024). Product lining pricing (0.457, 93.7% high effect), captive pricing (0.161, 96.21% high effect), and optional pricing strategy (0.252, 96.0% medium effect) were found to influence online purchase satisfaction (67.2%) (Abdulsalam et al., 2024). In the Nigerian e-commerce context, dynamic pricing AI has been identified as a practical solution to the challenges of currency fluctuations, rising logistics costs, and intense competition. AI-driven pricing strategies enable sellers to focus on customer service and sourcing quality products rather than manual price adjustments. Transparency in pricing, enabled by data-backed systems, has been identified as crucial for building consumer trust and turning one-time buyers into loyal advocates (Abdulsalam et al., 2024).

Business Performance and Retention in Akwa Ibom State

Empirical research conducted within Akwa Ibom State provides important context for understanding the business environment in which e-commerce enterprises operate. Abaikpa, Thomas, Daniel, and Udoh (2022) examined open innovation and organizational performance in selected firms in Akwa Ibom State, Nigeria. Their study contributes to understanding how innovative practices—including technological adoption such as ML-based pricing—can enhance organizational performance. The findings suggest that firms in Akwa Ibom State that embrace innovative approaches are better positioned to achieve superior performance outcomes. Abaikpa, Thomas, and Baridam (2022) investigated the

relationship between personality traits and employee outcomes, while Abaikpa, Baridam, and Uwa (2022) examined distributive justice and employee turnover among bank workers in Akwa Ibom State. These studies on employee retention provide valuable parallels to customer retention in e-commerce. Just as distributive justice and personality factors influence employee turnover, pricing fairness and personalised experiences influence customer churn. The application of machine learning to dynamic pricing can be understood as a mechanism for achieving pricing justice and personalisation that enhances customer retention. Abaikpa, Thomas, Udom, and Emmanuel (2023) conducted research on human capital management and organizational performance in United Bank for Africa Plc, further reinforcing the importance of strategic management practices for organizational success in Akwa Ibom State. The study's findings on the relationship between management practices and performance outcomes provide a foundation for understanding how e-commerce businesses can leverage ML-based dynamic pricing as a strategic management tool to enhance customer retention and overall business performance. Furthermore, Abaikpa (2025) examined the effect of performance management systems on small and medium enterprises in Uyo, Akwa Ibom State, Nigeria. The study's focus on SMEs is particularly relevant, as the majority of e-commerce businesses in Akwa Ibom State operate as SMEs. The findings suggest that systematic performance management—including data-driven pricing strategies—is essential for SME success and sustainability in the state's competitive business environment.

3. METHODOLOGY

3.1 Research Design

This study adopts a survey research design. The survey design is appropriate for investigating the relationship between machine learning-based dynamic pricing and customer retention among e-commerce businesses, as it allows for the collection of quantitative data from a representative sample of respondents. This design enables the researcher to describe the characteristics of the population, examine relationships between variables, and generalise findings to the broader population of e-commerce businesses in Akwa Ibom State.

3.2 Study Area

The study is conducted in Akwa Ibom State, Nigeria. Akwa Ibom State is located in the South-South geopolitical zone of Nigeria and has emerged as a growing hub for digital commerce. The state has witnessed increasing e-commerce activities, evidenced by the launch of Easy Pay Shop, a homegrown e-commerce platform designed to boost MSMEs and promote Made-in-Akwa-Ibom products (Akwa Ibom Unveils Easy Pay Shop, 2025). Additionally, there are 15 live Shopify stores operating in Akwa Ibom State, with two based in Eket (Shopify Stores in Akwa Ibom, Nigeria, 2026). The state government has demonstrated commitment to supporting digital businesses, as seen in the collaboration with platforms like Spangler Market to empower entrepreneurs. The growing digital economy infrastructure and increasing e-commerce participation make Akwa Ibom State an appropriate context for this study.

3.3 Population of the Study

The population of this study comprises all registered e-commerce businesses operating in Akwa Ibom State. This includes online retail platforms, digital marketplace operators (such as the state-backed Easy Pay Shop platform), and e-commerce-enabled Micro, Small, and Medium Enterprises (MSMEs) operating within the state. Given the emerging nature of the e-commerce sector, a comprehensive list of solely "e-commerce" businesses is not centrally published. Therefore, the study's population is operationally defined as all registered small and medium-sized enterprises (SMEs) in Akwa Ibom State that are engaged in digital commerce. According to the Directorate of SMEs of Akwa Ibom State, the total number of registered SMEs in the state was 11,990 as of 2021. This figure provides the most reliable and specific foundation for the population of this study.

3.4 Sampling Technique and Sample Size

A purposive sampling technique was employed to select respondents for this study. This approach allows the researcher to specifically target e-commerce business owners and managers who have direct involvement in pricing decisions and customer retention strategies. Using the Taro Yamane formula (a standard statistical formula for calculating sample size) on the population of 11,990 registered SMEs—a method previously validated in similar research on SMEs in Akwa Ibom State—a sample size of 400 respondents was determined. This sample size ensures adequate representation of the registered business population in the state. The 400 respondents will be strategically drawn from businesses operating through various digital channels, including Easy Pay Shop, Shopify (of which there are 15 known live stores in Akwa Ibom), and other digital commerce platforms identified within the state.

3.5 Instrument for Data Collection

Data were collected using a structured questionnaire titled "Machine Learning-Based Dynamic Pricing and Customer Retention among E-commerce Businesses in Akwa Ibom State, Nigeria. MLBDPCREBQ)" developed by the researcher.

3.6 Method of Data Analysis

Data collected from the questionnaire were analysed using both descriptive and inferential statistical techniques. Descriptive statistics including frequencies, percentages, means, and standard deviations were used to summarise respondents' demographic characteristics and responses to questionnaire items. Inferential statistics, specifically Pearson Product-Moment Correlation Coefficient, was employed to test the hypothesis regarding the relationship between machine learning-based dynamic pricing and customer retention. The Statistical Package for Social Sciences (SPSS) was used for data analysis, with the level of significance set at 0.05. The null hypothesis would be rejected if the p-value is less than 0.05, indicating a statistically significant relationship between ML-based dynamic pricing and customer retention.

4. DATA PRESENTATION, ANALYSIS AND DISCUSSION OF FINDINGS

This section presents the analyses of the data collected for the study and the discussion of the findings. The data were presented using tables and analyzed using the methods of analyses laid down in the methodology.

4.1. Presentation of Data

This section is basically designed to present, analyze and interpret the primary data obtained via the questionnaire which was purposively administered to the respondents. These are shown in the table below:

Table: 1: Number of questionnaire copies administered and returned

		Percentage
Copies of Questionnaire Administered	400	
Copies of Questionnaire Retrieved	389	97.2
Copies of Questionnaire not Retrieved	11	2.8
Total		100

Source: Fieldwork, 2026

From the Table, out of 400 questionnaires administered, 389 representing 97.2% were successfully returned. Eleven (11) copies of questionnaire representing 2.8 % were not returned.

Table 2 Percentage analysis of the Responses on machine learning-based dynamic pricing

machine learning-based dynamic pricing	SA 5	A 4	D 3	SD 2	UN 1	Total
Our e-commerce business has fully adopted and integrated machine learning algorithms into our pricing system to automatically adjust product prices in real-time.	95 (24.4%)	137 (35.2%)	81 (20.8%)	56 (14.4%)	20 (5.1%)	389 (100%)
Our machine learning system frequently updates product prices (daily or more often) to respond swiftly to changes in market conditions and consumer demand.	90 (23.1%)	149 (38.3%)	94 (24.2%)	44 (11.3%)	12 (3.1%)	389 (100%)
Our ML-based dynamic pricing system effectively integrates multiple factors such as competitor pricing, inventory levels, demand patterns, and customer behavior when determining optimal prices.	100 (41.6%)	162 (41.6%)	84 (21.6%)	32 (8.2%)	11 (2.8%)	389 (100%)
Our e-commerce platform utilizes machine learning to offer personalized prices or tailored discounts to different customer segments based on their unique purchase history and preferences.	138 (35.5%)	130 (33.4%)	60 (15.4%)	34 (8.7%)	27 (6.9%)	389 (100%)
Our machine learning pricing system is highly effective in achieving its objectives, including maximizing revenue, increasing sales volume, and maintaining competitive advantage in the market.	103 (26.5%)	140 (36.0%)	66 (17.0%)	40 (10.3%)	40 (10.3%)	389 (100%)

Source: Researcher's computation (2026)

The percentage analysis presented in Table 2 examined respondents' perceptions of machine learning-based dynamic pricing among e-commerce businesses. For the statement that the e-commerce business has fully adopted and integrated machine learning algorithms into its pricing system to automatically adjust product prices in real time, 24.4% of the respondents strongly agreed and 35.2% agreed, representing a combined 59.6% positive response. Meanwhile, 20.8% disagreed, 14.4% strongly disagreed, and 5.1% were undecided. This suggests that most respondents believe their organizations have embraced machine learning for automated pricing decisions.

Regarding the statement that the machine learning system frequently updates product prices to respond to market conditions and consumer demand, 23.1% strongly agreed and 38.3% agreed, giving a combined 61.4% agreement. Conversely, 24.2% disagreed, 11.3% strongly disagreed, and 3.1% were undecided. These findings indicate that respondents generally perceive their organizations as actively using machine learning to implement timely and responsive pricing adjustments.

On whether the ML-based dynamic pricing system effectively integrates competitor pricing, inventory levels, demand patterns, and customer behaviour when determining optimal prices, 25.7% strongly agreed and 41.6% agreed, representing an overall 67.3% positive response. In contrast, 21.6% disagreed, 8.2% strongly disagreed, and 2.8% remained undecided. This demonstrates that respondents acknowledge the capability of machine learning systems to process multiple market variables in making pricing decisions.

The analysis further revealed that 35.5% of respondents strongly agreed and 33.4% agreed that their e-commerce platforms use machine learning to provide personalized prices or tailored discounts based on customers' purchase histories and preferences, resulting in 68.9% overall agreement. However, 15.4% disagreed, 8.7% strongly disagreed, and 6.9% were undecided. This finding suggests that personalized pricing strategies supported by machine learning are becoming increasingly common within e-commerce businesses.

Concerning the statement that the machine learning pricing system is highly effective in achieving objectives such as maximizing revenue, increasing sales volume, and maintaining competitive advantage, 26.5% strongly agreed and 36.0%

agreed, representing a combined 62.5% positive response. On the other hand, 17.0% disagreed, 10.3% strongly disagreed, and 10.3% were undecided. This indicates that the majority of respondents perceive machine learning-based dynamic pricing as an effective strategic tool for improving organizational performance and competitiveness.

Table 3 Percentage analysis of the Responses on Customer Retention

Customer Retention	SA 5	A 4	D 3	SD 2	UN 1	Total
Since implementing ML-based dynamic pricing, we have witnessed a significant increase in the rate of repeat purchases among our existing customers.	157 (40.4%)	94 (24.2%)	94 (24.2%)	28 (7.2%)	16 (4.1%)	389 (100%)
Our customers demonstrate strong loyalty to our platform and consistently prefer us over competitors because they perceive our dynamically adjusted prices as fair and competitive.	130 (33.4%)	119 (30.6%)	80 (20.6%)	42 (10.8%)	18 (4.6%)	389 (100%)
The adoption of ML-driven dynamic pricing has contributed significantly to a noticeable reduction in our monthly customer churn rate (customers who discontinue purchasing from us).	100 (41.6%)	162 (41.6%)	84 (21.6%)	32 (8.2%)	11 (2.8%)	389 (100%)
We have observed a measurable increase in the average lifetime value of our customers, which we directly attribute to the dynamic pricing strategies enabled by our ML system.	95 (24.4%)	137 (35.2%)	81 (20.8%)	56 (14.4%)	20 (5.1%)	389 (100%)
Our customers are more willing to recommend our e-commerce platform to others and actively refer new customers because they trust our pricing to be consistently competitive and transparent.	141 (36.2%)	103 (26.5%)	90 (23.1%)	43 (11.1%)	12 (3.1%)	389 (100%)

Source: Researcher's computation (2025)

Table 3 presents the percentage distribution of respondents' opinions on customer retention in relation to the implementation of machine learning (ML)-based dynamic pricing. For the statement that since implementing ML-based dynamic pricing, the organization has witnessed a significant increase in the rate of repeat purchases among existing customers, 40.4% of the respondents strongly agreed and 24.2% agreed, representing a combined 64.6% positive response. Conversely, 24.2% disagreed, 7.2% strongly disagreed, while 4.1% were undecided. This finding suggests that most respondents believe ML-based dynamic pricing has encouraged customers to make repeat purchases.

Regarding the statement that customers demonstrate strong loyalty to the platform and consistently prefer it over competitors because they perceive dynamically adjusted prices as fair and competitive, 33.4% strongly agreed and 30.6% agreed, giving a combined 64.0% agreement. However, 20.6% disagreed, 10.8% strongly disagreed, and 4.6% were undecided. This implies that respondents generally perceive fair and competitive dynamic pricing as a key driver of customer loyalty.

For the statement that the adoption of ML-driven dynamic pricing has significantly reduced the monthly customer churn rate, 25.7% strongly agreed and 41.6% agreed, representing an overall 67.3% positive response. In contrast, 21.6% disagreed, 8.2% strongly disagreed, while 2.8% were undecided. These findings indicate that respondents believe machine learning-based pricing strategies have contributed to retaining customers by reducing the likelihood of customer defection.

Concerning the statement that there has been a measurable increase in customers' average lifetime value directly attributable to ML-enabled dynamic pricing, 24.4% strongly agreed and 35.2% agreed, resulting in a combined 59.6%

positive response. Meanwhile, 20.8% disagreed, 14.4% strongly disagreed, and 5.1% were undecided. This suggests that respondents generally acknowledge the contribution of machine learning-based pricing strategies to increasing long-term customer value.

Finally, regarding the statement that customers are more willing to recommend the e-commerce platform to others because they trust its pricing to be competitive and transparent, 36.2% strongly agreed and 26.5% agreed, representing a total of 62.7% agreement. On the other hand, 23.1% disagreed, 11.1% strongly disagreed, and 3.1% were undecided. This indicates that competitive and transparent pricing has enhanced customers' willingness to recommend the platform, thereby strengthening customer retention through positive word-of-mouth.

4.2. Testing of Hypothesis

There is no significant relationship between machine learning-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State, Nigeria.

Table 4: Linear regression analysis showing influence of machine learning-based dynamic pricing and customer retention among e-commerce businesses in Akwa Ibom State, Nigeria.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.728 ^a	.530	.529	.50988

Predictors: (Constant), machine learning-based dynamic pricing

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	113.575	1	113.575	436.864	.000 ^b
	Residual	100.611	387	.260		
	Total	214.186	388			

a. Dependent Variable: customer retention

b. Predictors: (Constant), machine learning-based dynamic pricing

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.027	.123		8.337	.000
	machine learning-based dynamic pricing	.700	.033	.728	20.901	.000

a. Dependent Variable: customer retention

Source: Researcher's Computation (2026)

The regression analysis examined the effect of machine learning-based dynamic pricing on customer retention. The model produced a correlation coefficient ($R = 0.728$), indicating a strong positive relationship between machine learning-based dynamic pricing and customer retention.

The coefficient of determination ($R^2 = 0.530$) shows that 53.0% of the variation in customer retention is explained by machine learning-based dynamic pricing, while the remaining 47.0% is attributable to other factors not included in the model. The Adjusted R^2 of 0.529 confirms that the explanatory power of the model remains stable after adjusting for the predictor variable, indicating that the model has good predictive capability. The standard error of the estimate (0.50988) indicates a relatively low level of prediction error, suggesting that the model provides a reasonably accurate estimate of customer retention.

The ANOVA results indicate that the regression model is statistically significant. The model recorded an F-statistic of 436.864 with a significance level of $p = 0.000$ ($p < 0.05$). This demonstrates that machine learning-based dynamic pricing significantly predicts customer retention and that the overall regression model provides a good fit for the data.

The regression coefficient for machine learning-based dynamic pricing is $B = 0.700$, with a standardized Beta coefficient of 0.728, a t-value of 20.901, and a p-value of 0.000.

This indicates that machine learning-based dynamic pricing has a positive and statistically significant effect on customer retention. Specifically, a one-unit improvement in machine learning-based dynamic pricing is associated with a 0.700-unit increase in customer retention. The standardized Beta coefficient of 0.728 suggests that the predictor has a strong influence on the dependent variable. This equation implies that when machine learning-based dynamic pricing is improved by one unit, customer retention increases by 0.700 units, assuming all other factors remain constant.

4.3. Discussion of Finding

The findings of this study revealed that machine learning-based dynamic pricing has a positive and statistically significant effect on customer retention. The regression analysis produced a strong positive correlation coefficient ($R = 0.728$), indicating that the adoption of machine learning-driven dynamic pricing is strongly associated with higher levels of customer retention among e-commerce firms. The coefficient of determination ($R^2 = 0.530$) further demonstrated that machine learning-based dynamic pricing accounted for 53.0% of the variation in customer retention, highlighting its substantial contribution to customers' willingness to continue purchasing from the same platform. The significant F-statistic (436.864; $p < 0.05$) and the positive regression coefficient ($\beta = 0.700$; $t = 20.901$; $p < 0.001$) confirmed that improvements in machine learning-based dynamic pricing significantly increase customer retention. This finding suggests that organizations that leverage machine learning algorithms to optimize prices in real time are more likely to retain customers by offering competitive, personalized, and market-responsive prices.

The findings are consistent with the work of Chen, M., Mao, S., and Liu, Y. (2022), who reported that machine learning-driven pricing systems enhance customer satisfaction and loyalty by accurately predicting consumer demand and adjusting prices to reflect market conditions. Their study argued that intelligent pricing algorithms improve customers' perceptions of fairness and value, thereby strengthening long-term customer relationships. Similarly, Wedel, M. and Kannan, P. K. (2016) emphasized that predictive analytics and machine learning enable firms to personalize prices and marketing offers, resulting in higher customer engagement, repeat purchases, and retention. The results also support the findings of Shankar, V. (2021), who found that artificial intelligence applications, including machine learning-based pricing, improve customer experience by providing timely and personalized value propositions. According to the author, customers are more likely to remain loyal to firms that consistently offer relevant prices based on changing market conditions and individual purchasing behaviour. Likewise, Davenport, T. H., Guha, A., and Grewal, D. (2021) concluded that AI-enabled pricing strategies significantly enhance customer lifetime value and retention by allowing organizations to respond proactively to fluctuations in demand, competitor pricing, and customer preferences.

5. CONCLUSION AND RECOMMENDATIONS

This study concludes that machine learning-based dynamic pricing has a significant positive effect on customer retention among e-commerce businesses in Akwa Ibom State. The findings confirm that real-time, personalised pricing strategies driven by machine learning algorithms enhance customers' perceptions of value and fairness, thereby increasing their loyalty and repeat purchase behaviour. Based on this, it is recommended that e-commerce firms invest in machine learning capabilities to optimise pricing dynamically, ensuring competitiveness and responsiveness to market fluctuations. Technology developers should focus on creating affordable and user-friendly pricing solutions tailored to the local market context. Additionally, policymakers could support digital transformation initiatives that encourage the adoption of AI-driven tools among small and medium-sized e-commerce enterprises to foster growth and customer loyalty.

REFERENCES

- Abaikpa, U. A. (2025). Effect of Performance Management Systems on Small and Medium Enterprises in Uyo, Akwa Ibom State, Nigeria. *African Journal of Commercial Studies*, 6(3).
- Abaikpa, U. A., Baridam, D., & Uwa, K. (2022). Distributive Justice and Employee Turnover among Bank Workers in Akwa Ibom State, Nigeria. *International Journal of Business and Management Review*, 10(5), 26-85.
- Abaikpa, U. A., Brownson, M. A., Enang, I. B., & Kumbur, M. D. (2026). Effect of Cashless Policies on Operations of Market Women in Akpan Andem Market, Uyo, Akwa Ibom State. *African Journal of Commercial Studies*, 7(4), 20-30. <https://doi.org/10.59413/ajocs/v7.i4.4>
- Abaikpa, U. A., Thomas, C. D., & Baridam, D. (2022). Personality Traits and Employee Outcomes. *British Journal of Multidisciplinary and Advanced Studies*.
- Abaikpa, U. A., Thomas, C. D., Daniel, S. D., & Udoh, U. N. (2022). Open Innovation and Organizational Performance in Selected Firms in Akwa Ibom State, Nigeria. *International Journal of Social Science Humanity & Management Research*, 1(6), 198-211.
- Abaikpa, U. A., Thomas, C. D., Udom, S. D., & Emmanuel, O. E. (2023). Human Capital Management and Organizational Performance in United Bank for Africa Plc.
- Abaikpa, U. A., Thomas, C. D., & Udoh, U. N. (2024). Human Capital Management and Organizational Performance in United Bank for Africa Plc. Uyo, Akwa Ibom State. *British Journal of Multidisciplinary and Advanced Studies*, 5(5), 55-76. <https://doi.org/10.37745/bjmas.2022.04191>
- Abaikpa, U. A., Thomas, C. D., Udoh, U. N., & Udom, S. D. (2024). Emotional Intelligence and Organizational Performance in Commercial Banks in Uyo Metropolis, Akwa Ibom State. *British Journal of Multidisciplinary and Advanced Studies*, 5(5), 27-54. <https://doi.org/10.37745/bjmas.2022.04190>.
- Abdulsalam, T. A., Omolaja, R. A., Tajudeen, R. B., & Abdulazeez, S. O. (2024). Efficacy of Digital Pricing Strategies on Customer Buying Decisions in the E-Commerce Industry: A PLS-SEM Approach. *African Journal of Stability and Development (AJSD)*, 16(1), 73-123. <https://doi.org/10.53982/ajsd.2024.1501.03-j>
- Ahn, J., Hwang, J., Kim, D., Choi, H., & Kang, S. (2020). A survey on churn analysis in various business domains. *IEEE Access*, 8, 220816-220839.
- Akwa Ibom Unveils Easy Pay Shop To Power MSMEs, Jobs, Digital Trade. (2025, December 22). THEWILL. <https://thewillnews.com>
- Ardjmand, E., Izadi, E., Tavasoli, A., Moradi-Jamei, B., & Shakeri, H. (2025). Graph-embedded reinforcement learning for dynamic pricing and advertising under network effects. *Applied Soft Computing*, 114056.
- Chukwuemeka, C. (2023). Advancing machine learning frameworks for customer retention and propensity modeling in E-Commerce Platforms. *Semantic Scholar*.
- Dynamic Pricing Method in the E-Commerce Industry Using Machine Learning. (2024). MDPI.
- Dynamic Pricing Models in E-Commerce: Exploring Machine Learning Techniques to Balance Profitability and Customer Satisfaction. (2025). *IEEE Xplore*.
- Dynamic Pricing Optimization in E-Commerce Using AI and Machine Learning: A Comprehensive Framework for Demand Prediction and Revenue Maximization. (2025). *SSRN*.

- Fraija, A., Henao, N., Agbossou, K., Kelouwani, S., Fournier, M., & Nagarsheth, S. H. (2024). Deep reinforcement learning based dynamic pricing for demand response considering market and supply constraints. *Smart Energy*, 14, 100139.
- Hybrid Machine Learning and Deep Reinforcement Learning for Real-Time Dynamic Pricing in E-Commerce with Demand-Aware Optimization. (2026). IEEE Xplore.
- Joy, S., et al. (2024). BERT for sentiment analysis: Achieving 95% accuracy in processing complex feedback data.
- Khazaei, E., et al. (2024). ML methods for customer churn prediction: Profit-based evaluation metrics and ensemble models.
- Li, J., & Chen, B. (2025, March). A Deep Q-Learning Optimization Framework for Dynamic Pricing in E-Commerce. In *Proceedings of the 2025 4th International Conference on Cyber Security, Artificial Intelligence and the Digital Economy* (pp. 367–371).
- Ma, W. (2025, October). Deep Reinforcement Learning-Driven Dynamic Pricing Strategy Optimization for E-Commerce Platforms. In *Proceedings of the 2025 2nd International Conference on Digital Economy and Computer Science* (pp. 1332–1338).
- Machine Learning Based Churn Analysis for Sellers on the E-Commerce Marketplace. (2023). *International Journal of Mathematics and Computer in Engineering*, (2), 171-176.
- Machine Learning-driven Dynamic Pricing Strategies in E-Commerce. (2023). Semantic Scholar.
- Machine Learning-driven Pricing Strategies: Enhancing Revenue Growth and Profitability. (2023). *AIML Studies*.
- Machine Learning-Driven Dynamic Pricing System for E-Commerce Revenue Optimization. (2026). IEEE Xplore.
- Nomura, Y., Liu, Z., & Nishi, T. (2025). Deep Reinforcement Learning for Dynamic Pricing and Ordering Policies in Perishable Inventory Management. *Applied Sciences*, 15(5).
- Shopify Stores in Akwa Ibom, Nigeria. (2026). Store Leads. <https://storeleads.app>
- Sun, J., Wang, Z., Qiao, Z., & Li, X. (2024). Dynamic Pricing Model for E-commerce Products Based on DDQN. *Journal of Comprehensive Business Administration Research*, 1(3), 171–178.
- Thomas, C. D., Abaikpa, U. A., Daniel, S. D., & Akpan, I. I. (2024). Imperatives of Small-Scale Businesses and Employment Generation in Uyo Local Government Area, Akwa Ibom State. *International Journal of Contemporary Social Science Academia*.
- Using Machine Learning for Dynamic Pricing Strategies in Retail and Online Markets. (2026). IEEE Xplore. <https://xplorestaging.ieee.org>
- Wang, X., Xie, Y., Jian, L., Liu, W., & Lv, W. (2025). A Two-Stage Deep Reinforcement Learning-Driven Dynamic Discriminatory Pricing Model for Hotel Rooms with Fairness Constraints. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(4), 337.
- Ye, et al. (2023). How changes in pricing impact consumer behaviour, crucial for optimising profitability and competitiveness in online markets.
- Zeinali, M., Ramezani Asli, L., & Khalili, M. A. (2026). Integrating Business Intelligence and CRM Systems With a Machine Learning Approach for Predictive Customer Retention in E-Commerce. *The Scientific World Journal*. <https://onlinelibrary.wiley.com>

APPENDIX I

QUESTIONNAIRE

Please read carefully each of the statement below and tick to indicate your agreement or disagreement to each item. Each item has to do with responses on machine learning-based dynamic pricing practices and customer retention outcomes among e-commerce businesses in Akwa Ibom State. The level or degrees of your responses are: Strongly agree (SA), Agree (A), strongly disagree (SD), disagree (D) and Neutral (N).

S/N	MACHINE LEARNING-BASED DYNAMIC PRICING AND CUSTOMER RETENTION AMONG E-COMMERCE BUSINESSES IN AKWA IBOM STATE, NIGERIA	SA	A	SD	D	N
A	MACHINE LEARNING-BASED DYNAMIC PRICING					
1	Our e-commerce business has fully adopted and integrated machine learning algorithms into our pricing system to automatically adjust product prices in real-time.					
2	Our machine learning system frequently updates product prices (daily or more often) to respond swiftly to changes in market conditions and consumer demand.					
3	Our ML-based dynamic pricing system effectively integrates multiple factors such as competitor pricing, inventory levels, demand patterns, and customer behavior when determining optimal prices.					
4	Our e-commerce platform utilizes machine learning to offer personalized prices or tailored discounts to different customer segments based on their unique purchase history and preferences.					
5	Our machine learning pricing system is highly effective in achieving its objectives, including maximizing revenue, increasing sales volume, and maintaining competitive advantage in the market.					
B	CUSTOMER RETENTION AMONG E-COMMERCE BUSINESSES					
6	Since implementing ML-based dynamic pricing, we have witnessed a significant increase in the rate of repeat purchases among our existing customers.					
7	Our customers demonstrate strong loyalty to our platform and consistently prefer us over competitors because they perceive our dynamically adjusted prices as fair and competitive.					
8	The adoption of ML-driven dynamic pricing has contributed significantly to a noticeable reduction in our monthly customer churn rate (customers who discontinue purchasing from us).					
9	We have observed a measurable increase in the average lifetime value of our customers, which we directly attribute to the dynamic pricing strategies enabled by our ML system.					
10	Our customers are more willing to recommend our e-commerce platform to others and actively refer new customers because they trust our pricing to be consistently competitive and transparent.					