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"REVIEW PAPER ON E-COMMERCE PRICE PREDICTION USING MACHINE LEARNING"

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ABSTRACT

In the rapidly evolving domain of e-commerce, dynamic pricing plays a critical role in influencing consumer behavior and market competitiveness. This study explores advanced methodologies for predicting product prices using machine learning (ML) techniques. Leveraging supervised models such as regression, decision trees, random forests, and ensemble methods, price forecasting systems can provide real-time insights and future trend estimations. Integration of time series analysis enhances prediction accuracy, allowing consumers and sellers to make informed decisions. Additionally, web scraping and big data analytics augment these systems by continuously updating datasets from platforms like Amazon. The findings highlight that ensemble models and deep learning techniques, when optimized with algorithms like XGBoost or swarm intelligence, significantly improve price prediction accuracy. This research emphasizes the importance of intelligent pricing tools in e-commerce, fostering efficiency, personalized recommendations, and competitive advantage in a data-driven market.

Key Words: *E-commerce,Price Prediction, Machine Learning, Time Series Forecasting, Ensemble Learning.*

I. INTRODUCTION

The exponential growth of the e-commerce sector over the past decade has transformed how consumers interact with the retail environment. As online platforms continue to expand their offerings and user bases, the competition among sellers has become increasingly fierce. In this context, pricing emerges as a key differentiator, influencing not only customer purchase decisions but also seller profitability and market positioning. The dynamic nature of online pricing—driven by fluctuations in demand, supply chain factors, competitor actions, and consumer behavior—necessitates sophisticated, automated tools to monitor and forecast product prices effectively.

Traditional rule-based pricing strategies are no longer sufficient in this rapidly evolving digital landscape. Manual methods often fail to capture the real-time intricacies of the market, leading to either overpricing, which can deter buyers, or underpricing, which can erode margins. This gap has given rise to the increasing adoption of ML **and** AI techniques in the domain of price prediction and optimization within e-commerce. By leveraging large volumes of structured and unstructured data—from historical prices and product metadata to customer reviews and competitor trends—ML algorithms can uncover patterns and forecast future price movements with greater accuracy.

This review paper explores and synthesizes recent advancements in machine learning applications for e-commerce price prediction. The primary objective is to provide a consolidated understanding of how different ML models—ranging from classical regression techniques (such as Linear Regression**,** Ridge Regression**,** and Decision Trees**)** to more advanced ensemble methods (Random Forests**,** XGBoost**)** and deep learning architectures (**Long Short-Term** Memory (LSTM) and GRU networks**)—**are utilized to forecast product prices across various domains, including electronics, agriculture, and fashion.

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Recent studies reveal that ML-based price forecasting systems are not only effective in improving price accuracy but also in supporting decision-making for both buyers and sellers. For instance, several researchers have integrated web scraping techniques to collect live product data from platforms like Amazon, Flipkart, and Alibaba, and used this real-time data to build predictive models that recommend the best time to purchase products. Other works have incorporated external factors such as seasonal trends, marketing campaigns, and social media sentiment to enhance the robustness of the predictive models.

Moreover, hybrid approaches that combine time-series analysis with regression modeling, and the inclusion of Big Data Analytics (BDA) and optimization algorithms (e.g., Genetic Algorithms, Barracuda Swarm Optimization) have further pushed the boundaries of what is achievable in pricing intelligence. These tools are also increasingly being used in niche areas such as demand forecasting for perishable goods (like vegetables and fruits), and in personalized pricing models that take into account user behavior and purchasing power.

Despite the promising progress, several challenges persist. These include data quality and sparsity, cold-start problems for new products, scalability of ML models to large product catalogs, and ethical concerns around dynamic and personalized pricing. This review aims to identify such limitations while also pointing toward emerging trends and underexplored areas, such as neurosymbolic AI**,** federated learning**,** and continual learning**,** which offer potential solutions to current bottlenecks.

In sum, this paper presents a comprehensive examination of the state-of-the-art machine learning techniques employed in e-commerce price prediction. By synthesizing contributions from diverse research efforts, it offers valuable insights into model selection, system architecture, performance metrics, and future research directions—thereby serving as a foundation for both academic researchers and industry practitioners aiming to advance the science and application of predictive pricing in digital marketplaces.

Nowadays, thanks to the development of e-commerce, there is a wide variety of data available online. Typically, descriptive information like photos is still present, even when new goods don't have prior interaction data. On the flip side, you'll see a lot more user evaluation information on more established products. Being both visual and textual, e-commerce relies heavily on these two types of data. Traditional methods of price prediction, on the other hand, run into Citing this article Hua H. in the year 2024. Utilizing deep neural networks and variational mode decomposition for online product price prediction. Difficulty in providing sufficient backing for all-encompassing price prediction systems due to difficulties in deriving useful insights from text and visuals. Companies rely heavily on accurate product pricing predictions when making strategic decisions in today's complicated and unpredictable market economy. Market complexity, nonlinearity, and the lack of stationary time series features present numerous hurdles to traditional price forecasting methodologies (Cortez et al., 2018; Wang et al., 2020). Traditional linear models have a hard time reflecting the different behavioural patterns shown by product pricing over time, which is a fundamental drawback. Predicting commodity prices is a complex and important task in the world of online shopping. Price fluctuations are introduced by the dynamic life cycle of commodities (Agnello et al., 2020). While established commodities typically have a wealth of price history, newer ones may struggle with data scarcity when trying to forecast their future value owing to a lack of past interaction data. These differences may be too much for conventional price prediction systems to handle.

The majority of existing price forecasting algorithms stick to a single computational technique, ignoring the impact of the commodity life cycle. Nevertheless, the intricacies of price prediction for both new and established commodities may be too much for a single algorithm to handle, which could lead to subpar forecast results (Lago et al., 2021). As a result, a complete framework for price forecasting that incorporates many advanced forecasting methods is recommended. In order to improve the precision of price forecasts, this framework should be able to determine the stage of the commodity's life cycle using its attributes and past price data. Currently, media text sentiment, keyword, or event feature extraction is the main method for integrating unstructured data into price prediction. This requires forecasting futures prices at the same time. According to Pan and Zhou (2020), Ramkumar et al. (2023), and Sun et al. (2022), the core of relevant study is the skillful transformation of unstructured data into e-commerce product prediction.

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It is worth investigating the following points: firstly, there is a lot of noise in the extracted effective price features from things like analytical reports and social comments, which could affect the model's ability to spot price fluctuations. Secondly, current methods for extracting event features from text data require a lot of human annotations on certain corpora, which is prone to subjective judgment and could cause other relevant information to be overlooked. Lastly, there is still a lot of debate about how to combine structured price data with features from unstructured textual information. A number of research fail to take into consideration the fact that different studies use different financial indicator datasets, sentiment traits, and trading data when feeding into their prediction models. The decomposition integration process is said to be a great way to improve the accuracy of predictions in complex time series predictive modelling. Its core idea is to simplify modelling by dividing complicated time series into smaller, more manageable subsequences using signal decomposition algorithms (Da Silva RG et al., 2020). Doi: 10.7717/peerj-cs.2353, The Variational Wu (2024), PeerJ Computer Science. 2/22 In order to gain a more nuanced understanding of the implicit modes in the data, a signal processing approach called Mode Decomposition (VMD) skillfully breaks down complex signals into many eigenmodes. At the same time, the complex structure of the deep neural network (DNN) allows it to handle unstructured data, identify complex relationships in price fluctuations, and improve the accuracy of predictions by varying the input data (Güven¸c, Çetin & Ko¸cak, 2021). Deep neural networks (DNNs) are great at extracting features from images and text codes; this allows them to better adapt to dynamic changes in e-commerce product prices and discover nonlinear correlations. When it comes to predicting the prices of products sold on online marketplaces, the integration of VMD and DNN presents a novel method.

Table 1 Impact and Benefits of Machine Learning in E-commerce Price Prediction

Aspect	Impact	Benefits
Price Forecasting	Predicts future price trends based on historical data and market patterns	Helps buyers decide the best time to purchase; helps sellers adjust pricing
Customer Behavior Analysis	Learns from clickstream data, purchase history, and preferences	Enables personalized pricing and targeted recommendations
Demand Forecasting	Estimates future demand for products using time-series or regression models	Prevents overstocking or understocking; optimizes inventory
Dynamic Pricing	Automatically adjusts prices in real-time based on competition and demand	Maximizes revenue and improves competitiveness
Sales and Promotion Planning	Analyzes effectiveness of past promotions using ML models like PromotionLens	Optimizes discount strategies and boosts sales
Cost Optimization	Predictive analytics reduce manual pricing errors and operational delays	Lowers operational cost and increases efficiency
Real-time Decision Making	Supports quick adaptation to market changes via automated predictions	Increases responsiveness to trends and customer needs
Competitive Advantage	Gains insights into competitors' pricing strategies	Enhances strategic planning and market positioning
User Experience	Provides personalized deals and accurate price suggestions	Increases customer satisfaction and loyalty
Scalability	Handles vast product databases using big data and cloud ML models	Enables growth without performance compromise

Machine Learning Work and How to Use AI in E-commerce

Machine Learning is a subfield of AI that empowers computers to learn from experience. Simply, ML algorithms can be trained by processing huge datasets. As a result of such training, ML allows you to spot patterns and anomalies within all this data and predict many outcomes your company can use.

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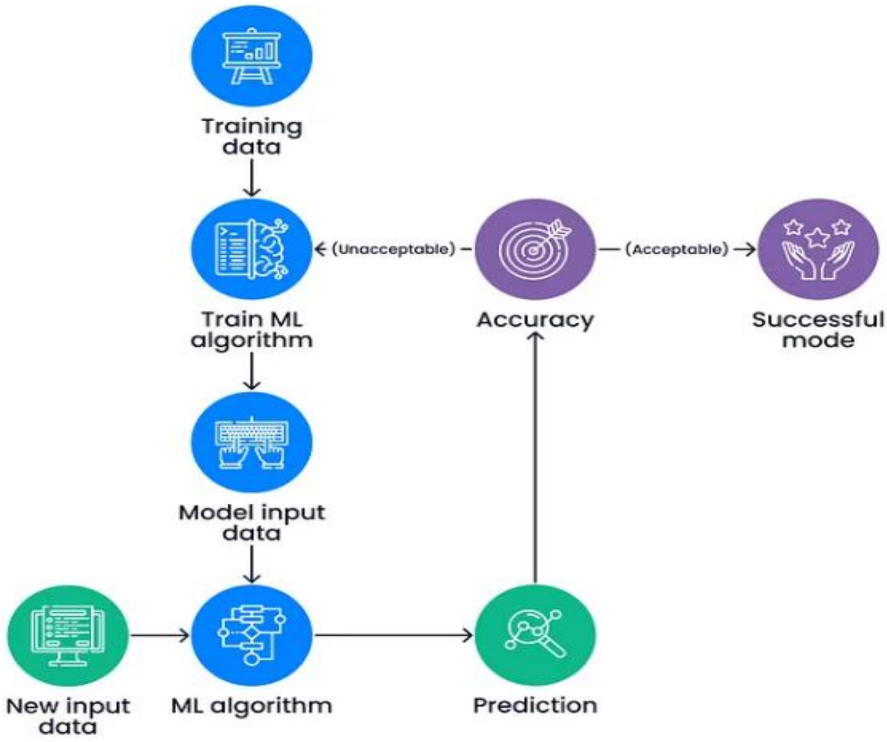

Fig. 1 AI in E-commerce

ML algorithms use computational methods to extract information from the data directly, so there is no need to rely on predetermined equations or models. These algorithms progressively enhance their performance as the volume of available samples for learning increases.

In the matter of E-commerce, machine learning opens many new opportunities for the retail industry by optimizing the customer experience, enabling greater flexibility, and establishing a robust digital presence. From enhancing simple processes to complex tasks, machine learning changes the E-commerce industry to meet better customer needs, which are constantly growing.[16]

Ecommerce pricing strategies

E-commerce pricing strategies play a crucial role in determining the success and profitability of online businesses by influencing customer perception, market positioning, and sales performance. Competitor pricing helps businesses stay relevant by matching or undercutting rival prices but can lead to profit margin erosion and price wars. Price skimming targets early adopters with high initial prices, maximizing early profits, but risks losing customers as competition increases. Dynamic pricing adjusts prices in real-time based on demand, seasonality, and market trends, offering profit flexibility but potentially creating negative customer perceptions if prices fluctuate too aggressively. Penetration pricing introduces products at low prices to quickly capture market share but may hurt brand value and customer loyalty if prices increase later. Value-based pricing focuses on customer-perceived value rather than production cost, allowing premium positioning but requiring deep market understanding. Psychological pricing uses tactics like ₹999 instead of ₹1000 to influence buyer perception, enhancing sales but sometimes viewed as deceptive. Bundle pricing combines multiple products at discounted rates to boost sales volume and improve inventory movement, though it can reduce per-item profitability. Loss leader pricing attracts customers with heavily discounted or loss-making items to drive traffic and encourage the purchase of more profitable products, but this strategy is risky if upselling fails. Each strategy has distinct advantages and challenges, and successful e-commerce businesses often tailor a mix of these approaches to match their market, competition, and customer expectations.[17]

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Table 2 Ecommerce pricing strategies

Pricing Strategy	Definition	Pros	Cons
Competitor Pricing	Setting prices based on competitors' prices (price matching or undercutting).	✓ Market competitiveness ✓ Customer perception ✓ Data-driven profitability	✗ Margin erosion ✗ Loss of differentiation ✗ Lack of control
Price Skimming	Setting high initial prices, then lowering over time.	✓ Profit maximization ✓ Quick investment recovery ✓ Premium product positioning	✗ Unsustainable long-term ✗ Vulnerable to competition
Dynamic Pricing	Real-time pricing based on demand, time, seasonality, and competition.	✓ Profit maximization ✓ Pricing flexibility	✗ Negative customer perception ✗ Requires complex technology
Penetration Pricing	Introducing products at low prices to quickly gain market share.	✓ Quick market entry ✓ Builds customer base	✗ Brand may appear low quality ✗ Customers may not remain loyal
Value-Based Pricing	Pricing based on the perceived value to the customer, not production costs.	✓ Differentiation ✓ Customer-centric approach	✗ Requires deep market understanding ✗ Complex pricing structure
Psychological Pricing	Pricing based on consumer behavior (e.g., ₹999 instead of ₹1000).	✓ Perceived value ✓ Increased sales through perception	✗ May seem deceptive ✗ Less effective for complex products
Bundle Pricing	Selling products in combined packages at discounted prices.	✓ Increases perceived value ✓ Boosts sales volume ✓ Inventory management	✗ Lower profit margins per item ✗ Customers may resist bundles
Loss Leader Pricing	Selling products at a loss to attract customers and drive additional sales.	✓ Increases traffic ✓ Potential to upsell profitable items	✗ Decreased immediate profits ✗ Risk if upselling fails

II. Literature Review

When it comes to predicting e-commerce data, the neural network algorithm shines because of how well it handles complex interactions. Researchers quickly use neural network models with different architectures to simulate nonlinear systems; these models have strong nonlinearity and large parallelism properties, making them particularly useful for time series analysis. To validate the improvement in prediction skills over linear models, Pandey et al. (2022) used ARIMA and a neural network based on radial basis functions to forecast exchange rates. In their study, Li et al. (2021) utilized a neural network with fewer hidden layer nodes to significantly reduce prediction error. Wu (2024) found that a lower termination condition led to an approximate 60% improvement. When it came to forecasting a product's success or failure, the five-layer DNN model developed by Deebak & AlTurjman (2022) performed better. The emergence of recurrent neural networks addresses the problem of DNN's inaccuracy in forecasting time series fluctuations. Using the long short-term memory (LSTM) approach, Issaoui et al. (2021) successfully predicted market trends in e-commerce.

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The results obtained by hybrid prediction algorithms are more satisfactory because real-world time series rarely follow strict linear or nonlinearities. Combining many methodologies and models improves prediction accuracy compared to adopting a single model, according to multiple research (Bukhari et al., 2020; Niu, Xu & Wang, 2020; Zhang & Chen, 2023) that highlight the importance of this topic. A study conducted by Tan et al. (2023) shown that DNN outperforms traditional approaches when it comes to capturing complex trends and seasonal changes in time series data. According to Sharma and Mehta (2024), DNN can improve forecast accuracy by building multi-level prediction models that incorporate various input features. These elements can include market sentiment data, technical indicators, and macroeconomic indicators. To further improve the accuracy of price forecasts, researchers have investigated the possibility of merging DNNs with additional machine learning techniques.

One approach that combines LSTM and DNN for stock price prediction was put up by Nanjappa et al. (2024). Based on their findings, this hybrid model is highly effective in capturing both immediate and distant relationships. For a more balanced distribution of input feature importance and improved prediction accuracy, other research has looked at DNN models that incorporate attention mechanisms (Li et al., 2024; Hu et al., 2024). The need of data preprocessing is magnified due to the non-stationary and non-linear nature of e-commerce product prices. Using a model designed for complicated, nonlinear, and irregularly distributed data, Gu (2023) attempted to forecast the pricing of products sold on e-commerce platforms.

The hybrid decomposition forecasting model that Osama et al. (2023) developed is able to capture the inherent nonlinearities and volatilities of time series. For data integrity, modal mixing, error reduction during reconstruction, and nonlinear data fitting, robustness tests were run. After decomposition, both linear and nonlinear data undergo reconstruction using a variety of strategies to improve prediction accuracy. A simple addition of model predictions is usually what linear integration is all about. On the other hand, nonlinear data, like product prices on e-commerce sites, is not well-suited to this method because it does not have a solid basis. To address this, intelligent models are currently used extensively for nonlinear sequence reconstruction. The idea that signals can adaptively produce intrinsic mode functions is the basis of Empirical Mode Decomposition (EMD), which is widely used for recursively breaking signals into separate, unknown modes (Campi, 2022). Academics have looked into other methods as EMD has its limits when it comes to noise and sampling sensitivity. An excellent solution to the problems with signal decomposition and a new direction for research was introduced by Dragomiretskiy and Zosso (2013) with Variational Modal Decomposition, which shows improved robustness to sampling and noise (Wu, 2024). By using the VMD technique to break down chaotic time series, Xu and Ren (2019) were able to greatly enhance their prediction capabilities. For the purpose of chaotic time series prediction, Guo et al. (2022) suggested combining the VMD method with a generalized neural network (GRNN). The results of the simulations showed that the VMD-GRNN model outperformed the EMD-GRNN model. A stacked recurrent neural network model was developed by Jiang, Han & Wang (2020) using the VMD algorithm. This model showed remarkable performance in terms of long-term prediction. Choosing the right modal number (K value) is crucial to the results of VMD decomposition, even if it has been shown to be effective. Analysis results could be tainted by an incorrect decision, such as too much or too little decomposition (He et al., 2021). Therefore, a crucial component for the broad use of VMD is choosing the right K value prior to decomposition. To solve the problem of choosing the optimal K value, Zhang et al. (2020) used VMD to break down wind speed time series and optimized the K value for decomposition using Sample Entropy estimates. The use of a binary function to evaluate similarity in sample entropy, however, can provide undesired or erroneous outcomes. According to Wang et al. (2023), when disruptions in the time series cause a higher level of uncertainty in the state values, the entropy value of the fuzzy system, which represents the complexity of the time series, increases. In addition, DNN outperform other machine learning algorithms in terms of computational capability, especially when dealing with big datasets. They can self-adapt, learn, and approximate complex nonlinear relationships thoroughly.

Pallab Banerjee et al. (2024): This study presents an advanced ecommerce price tracker with prediction capabilities using supervised ML models like regression and time series. It enables real-time price tracking and forecasting, helping users make informed decisions based on future pricing trends.

Yaodan Hu et al. (2022): The paper analyzes the impact of COVID-19 on e-commerce by examining stock prices of top companies in China and the US using LSTM and GRU models. Findings show a generally positive impact on e-commerce platforms despite short-term declines for some Chinese firms.

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Kirankumar Telkar et al. (2023): This research predicts laptop prices using ML models (Decision Tree, Ridge, Linear Regression, and an ensemble method). The ensemble model performed best. The system also scrapes Amazon data to assist users in making laptop purchasing decisions.

Hitesh Goyal et al. (2024): An ML-based system was developed to predict daily vegetable demand (okra and tomato) to reduce waste. Among four models, Decision Tree achieved 99.62% accuracy, making it the most effective for aiding e-commerce platforms in demand forecasting.

Sarah S. Alrumiah et al. (2021): This study highlights the role of Big Data Analytics (BDA) in e-commerce, improving vendor revenue and customer experience. It also notes challenges like high costs and data overload, despite BDA's positive impact on personalization and loyalty.

Latifah Almuqren et al. (2024): The paper introduces a WSN-assisted ML model (CP3-BSOADL) using a stacked auto-encoder and Barracuda Swarm Optimization to predict consumer purchasing power for interest-based e-commerce, achieving superior performance in personalization and pricing strategies.

Chenyang Zhang et al. (2022): The authors developed Promotion Lens, a visual analytics tool combining time-series forecasting and visualizations to evaluate promotion strategies' effectiveness in e-commerce. It supports scenario-based analysis and improves promotional planning.

Elias Dritsas et al. (2025): This survey reviews ML applications in e-commerce such as pricing, recommendation, fraud detection, and behavior analysis. It also discusses new approaches (FL, QML), challenges (scalability, privacy), and provides a roadmap for future research.

Table 3 Literature Review Summary Table – ML & Predictive Analytics in E-Commerce

Author(s)	**Year**	**Focus Area**	**Methods/Techniques**	**Key Contribution / Outcome**
Pallab Banerjee et al.	2024	E-commerce price prediction	Supervised ML, regression, time series analysis	Real-time price tracker with forecasting capabilities for better decision-making
Yaodan Hu et al.	2022	COVID-19 impact on e-commerce	LSTM and GRU neural networks on stock prices	Found positive long-term effects of pandemic on e-commerce based on predictive modeling
Kirankumar Telkar et al.	2023	Laptop price prediction	Linear Regression, Decision Tree, Ridge Regression, Ensemble (RF + XGB)	Ensemble model gave highest prediction accuracy (R^2=0.896); integrated web scraping
Hitesh Goyal et al.	2024	Agri-demand forecasting for e-commerce	Decision Tree, Logistic Regression, Random Forest, Linear Regression	Decision Tree yielded 99.62% accuracy in predicting vegetable demand
Sarah S. Alrumiah et al.	2021	Big Data Analytics in e-commerce	Literature review across 15 studies, analysis of BDA tools and impacts	Demonstrated how BDA enhances vendor competitiveness and customer experience
Latifah Almuqren et al.	2024	Interest-based e-commerce	WSNs, Deep Learning (SAE), Barracuda Swarm Optimization Algorithm (BSO)	Proposed CP3-BSOADL model for purchasing power prediction using real-time behavioral data
Chenyang Zhang et al.	2022	Promotion strategy evaluation	Time-series forecasting, visual analytics system (PromotionLens)	Enabled "what-if" promotion analysis and modeling for better sales strategy optimization
Elias Dritsas et al.	2025	ML in e-commerce (survey)	Review of ML/AI methods: FL, QML, CL, RL, Neurosymbolic AI	Offered taxonomy, real-world cases, and roadmap for future ML research in e-commerce

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III. Conclusion

In the digital era, where e-commerce platforms dominate global trade, pricing strategies play a pivotal role in shaping consumer behavior and ensuring market competitiveness. This review paper has systematically explored how machine learning (ML) and data-driven approaches are revolutionizing the way e-commerce businesses predict, monitor, and optimize product prices. From traditional regression models to cutting-edge deep learning architectures like LSTM and GRU, a diverse array of techniques has been developed to accurately forecast pricing trends based on historical data, user behavior, and market dynamics. Applications in sectors ranging from electronics and agriculture to stock market analysis demonstrate the versatility and impact of machine learning-based price prediction toolsHowever, several challenges remain—particularly regarding data quality, model interpretability, real-time processing, and the ethical use of dynamic pricing. Moreover, emerging trends such as federated learning, continual learning, and neurosymbolic AI offer promising avenues for addressing current limitations and unlocking new capabilities.machine learning has proven to be a transformative force in the field of e-commerce pricing. As the ecosystem continues to evolve, future research must focus on enhancing model transparency, ensuring fairness, and scaling systems to meet the demands of increasingly complex and dynamic markets. This review lays the groundwork for further innovations and sets the stage for developing more intelligent, responsive, and ethically grounded pricing systems in e-commerce.

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