



Open Access



Optimizing Dynamic Pricing through AI-Powered Real-Time Analytics: The Influence of Customer Behavior and Market Competition

Muhammad Awais¹

Abstract: *This study explores the role of AI-powered real-time analytics in enhancing the effectiveness of dynamic pricing strategies within competitive markets. Leveraging the growing relevance of artificial intelligence in business operations, the research investigates the direct impact of AI on pricing outcomes while assessing the moderating effects of customer behaviour and market competition intensity. Drawing on quantitative analysis, the study reveals that AI-driven pricing significantly improves pricing effectiveness, especially in highly competitive industries. However, price sensitivity among customers weakens the positive influence of AI, suggesting the need for businesses to carefully navigate AI applications in dynamic pricing. The study provides crucial insights for firms to enhance their real-time pricing strategies, emphasizing the significance of market competition and customer preferences. This study provides empirical evidence of AI's impact on pricing dynamics, contributes to the academic literature on AI integration in business models, and offers practical recommendations for businesses. The implications underscore the strategic advantage of AI in competitive environments yet caution against the indiscriminate use of dynamic pricing in markets with high customer price sensitivity. This study establishes a foundation for future research on the integration of AI in real-time pricing decisions and its broader impact on market competitiveness and consumer behaviour.*

Key Words: Dynamic Pricing, AI-Powered Real-Time Analytics, Customer Behavior, Market Competition, Business Operations

Introduction

In the ever-evolving digital landscape, businesses are increasingly reliant on advanced technologies to remain competitive. One of the most transformative technologies in recent years is artificial intelligence (AI), which has revolutionized various business processes, including customer service, supply chain management, and marketing (Paschek et al., 2017). Among its many applications, AI's role in dynamic pricing has emerged as one of the most significant and disruptive innovations in the e-commerce sector (Yang et al., 2022). Dynamic pricing, defined as the strategy of adjusting prices in real-time based on demand, competition, and other market factors, allows businesses to optimize their pricing strategies to maximize revenue while meeting consumer expectations (Kopalle et al., 2023). With the integration of AI, this process has evolved to become highly efficient, enabling companies to analyze vast amounts of real-time data and adjust prices instantaneously. The combination of AI with real-time analytics has made dynamic pricing more responsive and profitable, giving businesses a significant competitive edge in today's data-driven economy.

In the e-commerce industry, where pricing plays a crucial role in consumer purchase decisions, AI-powered dynamic pricing offers the ability to enhance revenue optimization, customer lifetime value (CLV), and overall customer satisfaction (Bertsimas & Perakis, 2006). Companies like Amazon, Uber, and Airbnb have successfully leveraged AI for dynamic pricing, adjusting prices based on real-time supply and demand factors, competitor pricing, and customer behaviour (Gazi et al., 2024). For instance, Uber's surge pricing mechanism uses AI to adjust fares based on demand levels in a given area, ensuring that the

¹ University of Massachusetts Amherst, Massachusetts, United States.

▪ **Corresponding Author:** Muhammad Awais (mawais.3211@gmail.com)

▪ **To Cite:** Awais, M. (2024). Optimizing Dynamic Pricing through AI-Powered Real-Time Analytics: The Influence of Customer Behavior and Market Competition. *Qlantia Journal of Social Sciences*, 5(3), 99–108.

<https://doi.org/10.55737/qjss.370771519>



company can match supply with demand while maximizing revenue. Similarly, e-commerce platforms frequently adjust product prices in response to changes in consumer demand, competition, and inventory levels. While large-scale companies have been quick to adopt AI-driven dynamic pricing strategies, small and medium-sized enterprises (SMEs) are still exploring how to effectively implement such systems due to challenges like limited resources, data availability, and market dynamics.

Background of the Study

The e-commerce industry has witnessed unprecedented growth over the last decade, driven by increased internet penetration, the rise of mobile commerce, and the global shift towards online shopping. According to recent studies, global e-commerce sales are projected to exceed \$6 trillion by 2024 (Vyas et al., 2023), highlighting the immense potential of this sector. However, this rapid growth has also intensified competition, compelling businesses to adopt innovative strategies to attract and retain customers. Pricing remains a key differentiator in e-commerce, directly influencing consumers' purchasing decisions. Traditionally, companies used static or fixed pricing models, which failed to account for real-time market conditions or customer behaviour, often leading to suboptimal revenue generation or missed opportunities (Borenstein et al., 2002).

The advent of AI and machine learning technologies has fundamentally transformed how businesses approach pricing. By processing real-time data, such as consumer purchasing patterns, inventory levels, competitor pricing, and external factors like seasonality, AI algorithms can dynamically adjust prices to meet demand while optimizing profit margins. AI-powered dynamic pricing systems offer several advantages, including increased sales, enhanced customer satisfaction, improved inventory management, and higher overall profitability (Chen & Chen, 2015). Despite these advantages, many smaller e-commerce platforms struggle to implement AI-driven pricing strategies due to barriers such as the high costs of AI systems, limited access to large datasets, and a lack of expertise in data analytics (Vyas et al., 2023).

The existing literature on dynamic pricing primarily focuses on large corporations and their use of AI to optimize pricing strategies (Dash et al., 2019). However, there is limited research exploring how small and medium-sized e-commerce platforms can benefit from AI-powered dynamic pricing, particularly in environments where competition is high and resources are limited. Moreover, while the technical aspects of dynamic pricing have been well-explored (Javanmard & Nazerzadeh, 2019), there is a gap in understanding how consumer behaviour, market conditions, and external factors moderate the effectiveness of these pricing strategies. This research aims to investigate the role of AI in powering real-time analytics for dynamic pricing in the e-commerce sector, with a focus on both large and small businesses.

Research Gap

Despite the significant advancements in AI and its applications in dynamic pricing, several critical gaps remain in the current body of knowledge. First, while large corporations like Amazon and Uber have been extensively studied in terms of their use of AI for dynamic pricing, there is a lack of empirical research on how small and medium-sized e-commerce enterprises (SMEs) can implement AI to optimize their pricing strategies (Vyas et al., 2023). SMEs face unique challenges, such as limited access to resources, smaller datasets, and less sophisticated technological infrastructure, making it difficult for them to fully leverage AI. Therefore, understanding how AI can be adapted to the specific needs and constraints of SMEs is crucial for expanding the application of dynamic pricing across the e-commerce industry.

Second, existing research has largely focused on the economic and technical aspects of AI-powered dynamic pricing, such as profit optimization and pricing algorithms. However, there is a limited exploration of how consumer behaviour interacts with AI-driven pricing decisions (Basal et al., 2024). Understanding how customers respond to dynamically adjusted prices in real time and how factors like price sensitivity and purchase patterns influence AI pricing outcomes is critical for businesses aiming to balance profitability with customer satisfaction.

Finally, while real-time analytics powered by AI has become a key component of dynamic pricing, there is a lack of comprehensive studies that investigate how businesses can effectively harness real-time

data to make pricing decisions. Most studies have focused on predictive models or rule-based pricing systems, which do not fully utilize the capabilities of AI for continuous, real-time adjustments (Basal et al., 2024). This research aims to address these gaps by providing empirical evidence on the effectiveness of AI-powered real-time analytics for dynamic pricing in the e-commerce industry, with a particular focus on SMEs.

Research Objectives

The primary objective of this research is to investigate the role of AI-powered real-time analytics in optimizing dynamic pricing strategies in the e-commerce sector. Specifically, the study seeks to explore the impact of AI-driven pricing on key performance indicators such as revenue, profit margins, customer satisfaction, and inventory management. By examining the relationship between AI-powered analytics and pricing effectiveness, the research aims to provide insights into how e-commerce businesses, both large and small, can maximize their pricing potential in highly competitive environments.

Research Questions

To address the research objectives, this study will focus on the following key research questions:

RQ1. How does AI-powered real-time analytics impact the effectiveness of dynamic pricing strategies in e-commerce, particularly in terms of profitability and customer satisfaction?

RQ2. How do customer behaviour, including purchase patterns and price sensitivity, influence the outcomes of AI-driven dynamic pricing in the e-commerce industry?

So, it could be stated that this study provides empirical evidence on the effectiveness of AI-driven pricing strategies, offering practical insights for e-commerce businesses looking to implement or improve dynamic pricing models powered by AI.

Literature Review

AI-Powered Real-Time Analytics and Dynamic Pricing Effectiveness

The application of artificial intelligence (AI) in real-time analytics has significantly advanced the field of dynamic pricing, particularly in the e-commerce sector. Dynamic pricing, as a strategy, involves the continuous adjustment of prices based on real-time market data, including factors like demand fluctuations, competitor pricing, and customer behaviour (Mageshkumar et al., 2024). The integration of AI into this process allows businesses to leverage vast amounts of data to optimize pricing strategies in real time (Garbarino & Lee, 2003), leading to improved revenue management and customer satisfaction at longer run.

Research studies have also shown that AI-powered dynamic pricing systems can significantly enhance pricing effectiveness by making more accurate and timely pricing decisions than traditional methods. For instance, Chen and Folly (2022) highlight that AI algorithms, through machine learning and predictive analytics, can identify patterns in customer behaviour and market trends that would be impossible for humans to detect. This capability enables businesses to respond to market changes instantly, thereby maximizing profits and maintaining competitive pricing.

However, the effectiveness of AI-powered dynamic pricing is not uniform across all business types. Larger e-commerce firms, such as Amazon and Walmart, have successfully implemented AI-driven pricing strategies due to their access to vast datasets and sophisticated technological infrastructure (Kumar et al., 2024). These companies have the resources to continuously update their pricing models based on real-time data, leading to a significant competitive advantage. On the other hand, small and medium-sized enterprises (SMEs) often struggle with implementing such systems due to resource constraints, limited access to high-quality data, and the high cost of AI (Garbarino & Lee, 2003).

Existing literature has also emphasized the importance of customer-centric AI models in dynamic pricing. According to Thandekkattu and Kalaiarasi (2022), dynamic pricing strategies that are solely focused on profit maximization can lead to customer dissatisfaction and loss of loyalty if not carefully



managed. AI-powered systems that incorporate customer feedback and behavioural data into pricing decisions can help mitigate these risks by ensuring that prices are perceived as fair and justified by customers (Mageshkumar et al., 2024). This customer-centric approach is crucial in maintaining long-term customer relationships and ensuring the sustainability of dynamic pricing strategies. Based on the above discussion, the following is hypothesized:

Hypothesis 1: AI-powered real-time analytics positively impacts the effectiveness of dynamic pricing strategies in the e-commerce sector, leading to higher profitability and customer satisfaction.

Customer Behavior and AI-Driven Dynamic Pricing

Understanding customer behaviour is crucial for the successful implementation of AI-driven dynamic pricing. Customer behaviour, including purchase patterns and price sensitivity, plays a significant role in how dynamic pricing strategies are perceived and accepted by consumers (Faris & Batra, 2024). AI systems, through machine learning algorithms, can analyze historical data on customer purchases, browsing behaviour, and response to price changes to predict future behaviour and adjust prices accordingly.

One of the key aspects of customer behaviour that influences dynamic pricing is price sensitivity. Price-sensitive customers are more likely to respond to price changes, making them a primary target for dynamic pricing strategies (Nunan & Di Domenico, 2022). AI systems can segment customers based on their price sensitivity, allowing businesses to tailor pricing strategies to different customer segments. For example, a customer who frequently searches for discounts may be offered a lower price, while a customer with a history of purchasing premium products may be less price-sensitive and, therefore, subject to higher prices.

Research has also explored the psychological aspects of dynamic pricing, particularly the concept of price fairness. Consumers may perceive frequent or significant price changes as unfair, leading to negative outcomes such as decreased customer satisfaction and brand loyalty (Quan et al., 2019). AI systems that incorporate behavioural economics principles can help mitigate these risks by ensuring that price changes are gradual and justified, thereby maintaining customer trust.

Another important consideration is the impact of AI-driven dynamic pricing on customer loyalty. While dynamic pricing can optimize revenue in the short term, it can also lead to customer churn if not carefully managed (McMurtrey & Kasowaki, 2023). AI systems can address this issue by incorporating loyalty programs and personalized offers into pricing strategies, thereby balancing short-term revenue optimization with long-term customer retention. Based on the above discussion, the following is hypothesized:

Hypothesis 2: Customer behaviour, including purchase patterns and price sensitivity, moderates the relationship between AI-driven dynamic pricing and its effectiveness in the e-commerce industry.

Moderating Factors: Market Competition Intensity and Product Type

The effectiveness of AI-powered dynamic pricing is also influenced by external factors such as market competition intensity and product type. In highly competitive markets, businesses are under constant pressure to adjust prices in response to competitors' actions, making real-time pricing adjustments crucial for maintaining market share (Chen et al., 2023). AI systems can provide businesses with a competitive edge by continuously monitoring competitor prices and adjusting their own prices accordingly.

Research has shown that the intensity of market competition can significantly impact the success of dynamic pricing strategies. In markets with low competition, businesses have more flexibility in setting prices, as there is less pressure to match competitors' prices (Moro-Visconti et al., 2023). However, in highly competitive markets, even small price differences can lead to significant shifts in customer demand, making real-time pricing adjustments essential.

Product type also plays a crucial role in determining the effectiveness of AI-driven dynamic pricing. For instance, products with high demand elasticity, such as consumer electronics, are more suitable for dynamic pricing strategies, as small price changes can significantly influence demand (Kopalle et al., 2023). On the other hand, products with low demand elasticity, such as luxury goods, may not benefit as much

from dynamic pricing, as consumers are less responsive to price changes. This discussion leads towards the following hypothesis:

Hypothesis 3: Market competition intensity and product type moderate the relationship between AI-powered real-time analytics and the effectiveness of dynamic pricing strategies.

Methodology

Research Design

This study employs a quantitative research design to investigate the relationship between AI-powered real-time analytics and the effectiveness of dynamic pricing strategies in the e-commerce sector. The research is cross-sectional, collecting data at a single point in time, which is ideal for identifying correlations and testing hypotheses related to AI implementation and pricing effectiveness. This study uses a deductive approach, testing hypotheses derived from existing literature to explore how AI-driven pricing impacts profitability and customer satisfaction and how customer behaviour and market competition moderate this relationship.

Population

The target population for this study comprises e-commerce businesses that use or are in the process of adopting AI-powered dynamic pricing systems. This includes businesses from various industries, such as consumer electronics, apparel, and consumer goods that frequently adjust prices based on market and customer data. These businesses are ideal for studying the effectiveness of AI in dynamic pricing due to their reliance on flexible pricing strategies and data analytics.

Sample Selection

A sample of 200 e-commerce business staff is selected for this study. This number is sufficient to capture diverse business sizes (small, medium, and large) and industry types while still being manageable for data collection and analysis. The sample is drawn using stratified random sampling, where the businesses are categorized based on their size (small, medium, and large enterprises) and the industry they operate in (e.g., consumer electronics, apparel, consumer goods). This stratification ensures that the study captures the variation in how AI-powered dynamic pricing is used across different business contexts, providing a comprehensive understanding of its effectiveness.

The chosen sample size balances practicality and statistical power, ensuring that the data is robust enough to perform reliable analyses while keeping the study focused and manageable. With 200 participants, the study can produce meaningful insights into the factors influencing dynamic pricing across various industries.

Data Collection Tool

The primary data collection tool for this study is a structured questionnaire specifically designed to measure the following key variables:

- AI-Powered Real-Time Analytics:** This section assessed how businesses use AI to adjust prices based on real-time data. It will cover the frequency of price changes, the types of data used (e.g., competitor pricing, customer behaviour), and the perceived effectiveness of the AI systems. Items are adapted from the framework developed by Lee and Monroe (2008) on dynamic pricing.
- Dynamic Pricing Effectiveness:** Questions in this section evaluated the outcomes such as profitability, revenue growth, and customer satisfaction resulting from the implementation of dynamic pricing strategies. The items were drawn from the work of Suresh et al. (2023) on pricing effectiveness.
- Customer Behavior:** This section measured the customer responses to price changes, their price sensitivity, and purchase behaviour. Items are adapted from the work of Kumar et al. (2019) on customer behaviour and pricing strategies.
- Market Competition Intensity:** Questions in this section captured the level of competition businesses face, with a focus on how quickly and frequently they must adjust prices in response to competitors. This section used items from Markopoulos and Hosanagar (2018).



The questionnaire utilized a Likert scale (e.g., 1 = strongly disagree, 5 = strongly agree) to measure perceptions and behaviours, making it easy to quantify and analyze the data. The tool was pre-tested on a small group of e-commerce professionals to ensure clarity and reliability before being distributed to the full sample.

Data Collection Method

Data was collected using online surveys, which were distributed to managers and business owners of e-commerce companies via email and professional networks (e.g., LinkedIn, industry groups). The online format ensures convenience and accessibility for respondents while also enabling broad geographical coverage. To encourage participation, respondents will be offered a summary of the study's findings as an incentive.

In addition to primary data collected through the survey, secondary data on market competition and business performance were gathered from publicly available industry reports and databases (e.g., Statista, market research publications). This secondary data supplemented the primary survey data, providing additional context for understanding the competitive pressures businesses face.

Data Analysis

Data were analyzed using SPSS software, which is well-suited for conducting statistical tests and regression analyses. The following steps guided the analysis procedure:

1. Descriptive statistics provided a summary of the sample's characteristics, such as company size, industry type, and levels of AI adoption in dynamic pricing.
2. Reliability and validity testing provided data about Cronbach's alpha, which is used to assess the internal consistency of the questionnaire items and ensure the reliability of measurements for AI-powered analytics, dynamic pricing effectiveness, customer behaviour, and market competition.
3. Correlation analysis explored the relationships between the key variables, particularly focusing on the impact of AI on dynamic pricing effectiveness.
4. Multiple regression analysis was used to test Hypothesis 1, examining the effect of AI-powered real-time analytics on dynamic pricing effectiveness. Additional regression models with interaction terms tested Hypotheses 2 and 3, assessing how customer behaviour and market competition moderate this relationship.
5. Hypothesis testing: A significance level of 0.05 is used to determine whether the relationships between variables are statistically significant, allowing for the acceptance or rejection of the hypotheses.

The results helped address the research questions and support or refute the proposed hypotheses.

Descriptive Statistics

Descriptive statistics give an overview of the sample data for each variable, including mean and standard deviation.

Table 1

Descriptive statistics

Variable	Mean	Standard Deviation	Min	Max
AI-powered real-time analytics (X1)	3.80	0.92	1	5
Dynamic pricing effectiveness (Y)	4.10	0.75	2	5
Customer behavior (X2)	3.50	0.88	1	5
Market competition intensity (X3)	3.90	0.95	1	5

The mean value for AI-powered real-time analytics is 3.80, indicating moderate use of AI in dynamic pricing decisions. Dynamic pricing effectiveness shows a higher mean value of 4.10, suggesting that firms perceive their dynamic pricing strategies as largely effective. Customer behaviour has a mean of 3.50, reflecting moderate price sensitivity, while market competition intensity has a mean of 3.90, indicating

that competition varies among the firms surveyed. These descriptive statistics offer a basic understanding of the data distribution and variability among the key variables in this study.

Correlation Analysis

The correlation matrix below demonstrates the relationships between the variables. The strength and direction of each relationship are indicated by correlation coefficients (r-values).

Table 2

Correlation analysis

Variable	AI-powered real-time analytics (X1)	Dynamic pricing effectiveness (Y)	Customer behavior (X2)	Market competition intensity (X3)
AI-powered real-time analytics (X1)	1.00	0.65	-0.10	0.45
Dynamic pricing effectiveness (Y)	0.65	1.00	-0.25	0.50
Customer behavior (X2)	-0.10	-0.25	1.00	-0.15
Market competition intensity (X3)	0.45	0.50	-0.15	1.00

The results indicate a strong positive correlation ($r = 0.65$, $p < 0.01$) between AI-powered real-time analytics and dynamic pricing effectiveness. This suggests that companies utilizing AI for pricing decisions tend to achieve more effective dynamic pricing outcomes. Customer behaviour has a moderate negative correlation with dynamic pricing effectiveness ($r = -0.25$, $p < 0.01$), implying that price-sensitive customers may undermine the effectiveness of AI-driven pricing. Lastly, market competition intensity positively correlates with both AI-powered analytics ($r = 0.45$, $p < 0.01$) and dynamic pricing effectiveness ($r = 0.50$, $p < 0.01$), indicating that more competitive environments benefit from AI-driven pricing strategies.

Regression Analysis

Regression analysis was performed to test the direct and moderating effects of AI-powered real-time analytics on dynamic pricing effectiveness. Table 3 summarizes the results of the multiple regression analysis.

Table 3

Regression analysis

Predictor	B	Standard Error	t-value	p-value	Significance
AI-powered real-time analytics (X1)	0.45	0.07	6.43	0.000	Significant
Customer behavior (X2)	-0.20	0.08	-2.50	0.013	Significant
Market competition intensity (X3)	0.35	0.09	3.89	0.001	Significant
Interaction (X1*X2)	-0.15	0.05	-3.00	0.005	Significant
Interaction (X1*X3)	0.20	0.06	3.33	0.002	Significant

The regression results indicate that AI-powered real-time analytics (X1) has a significant positive impact on dynamic pricing effectiveness ($B = 0.45$, $p < 0.001$), supporting Hypothesis 1. This finding implies that businesses that integrate AI into their pricing strategies achieve greater pricing effectiveness. Customer behaviour (X2) shows a significant negative moderating effect on this relationship ($B = -0.15$, $p < 0.05$), confirming Hypothesis 2. This suggests that in cases where customers are highly price-sensitive, the positive impact of AI on dynamic pricing is weakened. Lastly, market competition intensity (X3)



significantly moderates the relationship between AI-powered real-time analytics and dynamic pricing effectiveness ($B = 0.20, p < 0.01$), supporting Hypothesis 3. This result implies that firms operating in more competitive environments derive greater benefits from AI-powered pricing strategies, further enhancing their pricing effectiveness.

These results indicate that AI plays a crucial role in improving dynamic pricing effectiveness, but its success depends on customer behaviour and market competition. Specifically, firms targeting price-sensitive customers must adapt their AI strategies to maximize effectiveness, while firms in competitive markets can leverage AI to achieve greater pricing success.

Discussion

The results of this study offer valuable insights into the effectiveness of AI-powered real-time analytics in dynamic pricing, particularly in competitive markets and with varying levels of customer price sensitivity. The primary objective of this research was to examine how AI-driven pricing systems influence dynamic pricing effectiveness and to explore the moderating roles of customer behaviour and market competition intensity. The findings align with the research objectives and address the research questions posed.

First, the analysis demonstrates that AI-powered real-time analytics has a strong positive effect on dynamic pricing effectiveness, supporting Hypothesis 1. This suggests that the integration of AI in pricing decisions leads to more efficient and effective pricing strategies. The findings corroborate existing literature on AI's capability to process vast amounts of real-time data and predict optimal price points more accurately than traditional methods (Kopalle et al., 2023). The ability of AI to dynamically adjust prices based on market conditions and consumer demand explains the significant relationship between AI adoption and pricing success. This supports the research question about the direct effect of AI on dynamic pricing, confirming that AI is a valuable tool for businesses seeking to enhance their pricing efficiency.

Second, Hypothesis 2 proposed that customer behaviour, particularly price sensitivity, would moderate the relationship between AI-powered analytics and dynamic pricing effectiveness. The results indicate that when customers are more price-sensitive, the positive impact of AI on pricing effectiveness diminishes. This finding is in line with studies that highlight how customer reactions to dynamic pricing depend on perceived fairness and value (Alderighi et al., 2022). Businesses need to consider customer segments when deploying AI-driven pricing strategies. For price-sensitive customers, frequent or significant price fluctuations might lead to dissatisfaction, which can counteract the benefits of AI's precision in price optimization. Therefore, firms must carefully balance AI-driven price changes with customer expectations, providing transparency and ensuring perceived fairness.

Finally, Hypothesis 3 explored the role of market competition intensity in moderating the effect of AI-powered analytics on dynamic pricing effectiveness. The results reveal that AI-powered analytics is more effective in highly competitive markets, supporting the hypothesis. This finding highlights that in competitive industries, businesses are under more pressure to optimize pricing strategies in real time to maintain a competitive edge (Zamani et al., 2022). The ability of AI to continuously monitor and respond to competitors' pricing strategies enables businesses to remain competitive by adjusting their prices more efficiently than those relying on traditional pricing methods. Consequently, companies in fiercely competitive industries should prioritize the adoption of AI-powered analytics to outperform rivals.

Implications of the Study

The study has several practical and theoretical implications. From a practical perspective, the findings suggest that businesses, especially in competitive industries, should invest in AI-powered analytics to enhance dynamic pricing strategies. The positive impact of AI on pricing effectiveness is clear, but the success of these strategies depends on customer characteristics and market dynamics. For businesses targeting price-sensitive customers, the challenge lies in using AI to adjust prices without alienating customers. As AI becomes more prevalent in pricing systems, companies should also consider transparency and communication strategies to ensure customer trust and acceptance.

Theoretically, this study contributes to the growing body of research on AI applications in business operations. It provides empirical evidence for the role of AI in enhancing pricing decisions, particularly in dynamic markets. Additionally, the study introduces important moderating variables—customer behaviour and market competition—that influence the effectiveness of AI-powered pricing systems. This enriches the understanding of how contextual factors shape the outcomes of AI implementation in pricing.

Conclusion

In conclusion, this study demonstrates that AI-powered real-time analytics significantly improves dynamic pricing effectiveness. However, the success of these systems is contingent on market conditions and customer behaviour. While businesses in competitive environments benefit greatly from AI-driven pricing strategies, companies targeting price-sensitive customers must be mindful of how frequent or abrupt price changes might impact customer satisfaction. The findings suggest that AI is a powerful tool for optimizing pricing decisions, but its application must be carefully tailored to specific market and customer conditions to maximize its benefits. As AI continues to evolve, businesses that adapt to these emerging technologies will have a distinct advantage in optimizing pricing strategies in real time.

References

- Alderighi, M., Nava, C. R., Calabrese, M., Christille, J. M., & Salvemini, C. B. (2022). Consumer perception of price fairness and dynamic pricing: Evidence from Booking.com. *Journal of Business Research*, 145, 769–783. <https://doi.org/10.1016/j.jbusres.2022.03.017>
- Basal, M., Saraç, E., & Özer, K. (2024). Dynamic pricing strategies using artificial intelligence algorithm. *Open Journal of Applied Sciences*, 14(08), 1963–1978. <https://doi.org/10.4236/ojapps.2024.148128>
- Bertsimas, Dimitris, & Perakis, G. (2006). Dynamic pricing: A learning approach. In *Applied Optimization* (pp. 45–79). Kluwer Academic Publishers. https://doi.org/10.1007/0-387-29645-X_3
- Borenstein, S., Jaske, M., & Rosenfeld, A. (2002). Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets. *UC Berkeley: Center for the Study of Energy Markets*. <https://escholarship.org/uc/item/11w8d6m4>
- Chen, M., & Chen, Z.-L. (2015). Recent developments in dynamic pricing research: Multiple products, competition, and limited demand information. *Production and Operations Management*, 24(5), 704–731. <https://doi.org/10.1111/poms.12295>
- Chen, Q., & Folly, K. A. (2022). Application of artificial intelligence for EV charging and discharging scheduling and dynamic pricing: A review. *Energies*, 16(1), 146. <https://doi.org/10.3390/en16010146>
- Chen, J., Zhou, W., & Frankwick, G. L. (2023). Firm AI adoption intensity and marketing performance. *Journal of Computer Information Systems*, 1–18. <https://doi.org/10.1080/08874417.2023.2277751>
- Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability*, 14(3), 43–53. <https://doi.org/10.33423/jsis.v14i3.2105>
- Faris, W. F., & Batra, S. (2024). AI-Driven Dynamic Pricing Mechanisms for Demand-Side Management. *Acta Energetica*, (02), 82–94. <https://actaenergetica.org/index.php/journal/article/view/519>
- Garbarino, E., & Lee, O. F. (2003). Dynamic pricing in internet retail: Effects on consumer trust. *Psychology & Marketing*, 20(6), 495–513. <https://doi.org/10.1002/mar.10084>
- Gazi, M. S., Hasan, M. R., Gurung, N., & Mitra, A. (2024). Ethical Considerations in AI-driven Dynamic Pricing in the USA: Balancing Profit Maximization with Consumer Fairness and Transparency. *Finance and Accounting Studies*, 6(2), 100–111. <https://doi.org/10.32996/jefas.2024.6.2.8>
- Javanmard, A., & Nazerzadeh, H. (2019). Dynamic pricing in high-dimensions. *Journal of Machine Learning Research*, 20(9), 1–49. <http://arxiv.org/abs/1901.01030>



- Kumar, V., Ashraf, A. R., & Nadeem, W. (2024). AI-powered marketing: What, where, and how? *International Journal of Information Management*, 77(102783), 102783. <https://doi.org/10.1016/j.ijinfomgt.2024.102783>
- Kumar, V., Rajan, B., Gupta, S., & Pozza, I. D. (2019). Customer engagement in service. *Journal of the Academy of Marketing Science*, 47(1), 138–160. <https://doi.org/10.1007/s11747-017-0565-2>
- Kopalle, P. K., Pauwels, K., Akella, L. Y., & Gangwar, M. (2023). Dynamic pricing: Definition, implications for managers, and future research directions. *Journal of Retailing*, 99(4), 580–593. <https://doi.org/10.1016/j.jretai.2023.11.003>
- Lee, F., & Monroe, K. B. (2008). Dynamic Pricing on the Internet: A Price Framing Approach. *Advances in Consumer Research*, 35, 637.
- Mageshkumar, N. V., Rajkumar, N., Viji, C., & Mohanraj, A. (2024). AI-powered financial operation strategy for cloud computing cost optimization for the future. *Salud, Ciencia y Tecnología - Serie de Conferencias*, 3, 694. <https://doi.org/10.56294/sctconf2024694>
- Markopoulos, P. M., & Hosanagar, K. (2018). A model of product design and information disclosure investments. *Management Science*, 64(2), 739–759. <https://doi.org/10.1287/mnsc.2016.2634>
- McMurtrey, M., & Kasowaki, L. (2023). *Adaptive Pricing Strategies: How AI-Powered Electronic Shelf Labels Are Changing the Game* (No. 11082). EasyChair.
- Moro-Visconti, R., Cruz Rambaud, S., & López Pascual, J. (2023). Artificial intelligence-driven scalability and its impact on the sustainability and valuation of traditional firms. *Humanities & Social Sciences Communications*, 10(1), 1–14. <https://doi.org/10.1057/s41599-023-02214-8>
- Nunan, D., & Di Domenico, M. (2022). Value creation in an algorithmic world: Towards an ethics of dynamic pricing. *Journal of Business Research*, 150, 451–460. <https://doi.org/10.1016/j.jbusres.2022.06.032>
- Paschek, D., Luminosu, C. T., & Draghici, A. (2017). Automated business process management- in times of digital transformation using machine learning or artificial intelligence. In *MATEC web of conferences* (Vol. 121). EDP Sciences.
- Quan, J., Wang, X., & Quan, Y. (2019). Effects of consumers' strategic behaviour and psychological satisfaction on the retailer's pricing and inventory decisions. *IEEE Access: Practical Innovations, Open Solutions*, 7, 178779–178787. <https://doi.org/10.1109/access.2019.2958685>
- Suresh Kumar, S., Margala, M., Siva Shankar, S., & Chakrabarti, P. (2023). A novel weight-optimized LSTM for dynamic pricing solutions in e-commerce platforms based on customer buying behaviour. *Soft Computing*, 1–13. <https://doi.org/10.1007/s00500-023-08729-1>
- Thandekkattu, S. G., & Kalaiarasi, M. (2022). Customer-centric E-commerce implementing artificial intelligence for better sales and service. In *Proceedings of Second International Conference on Advances in Computer Engineering and Communication Systems* (pp. 141–152). Springer Nature Singapore.
- Vyas, S. K., Vyas, L., Singh, S., & Joshi, M. (2023). Future of E-Commerce: A Robust Review. In *Intelligent Sustainable Systems: Selected Papers of WorldS4 2022, Volume 2* (pp. 697–710). Singapore: Springer Nature Singapore.
- Yang, C., Feng, Y., & Whinston, A. (2022). Dynamic pricing and information disclosure for fresh produce: An artificial intelligence approach. *Production and Operations Management*, 31(1), 155–171. <https://doi.org/10.1111/poms.13525>
- Zamani, E. D., Griva, A., & Conboy, K. (2022). Using Business Analytics for SME business model transformation under pandemic time pressure. *Information Systems Frontiers: A Journal of Research and Innovation*, 24(4), 1145–1166. <https://doi.org/10.1007/s10796-022-10255-8>