The Impact of Big Data–Driven Dynamic Pricing Strategies on Purchase Behavior, Customer Satisfaction, and Repurchase Intention in Iranian Online Retail Stores Considering the Moderating Role of Customer Trust in the Platform

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Abstract: The present study aimed to examine the impact of big data–driven dynamic pricing strategies on purchase behavior, customer satisfaction, and repurchase intention in Iranian online retail stores while investigating the moderating role of customer trust in the platform. This research employed an applied quantitative approach using a correlational design based on structural equation modeling. The statistical population consisted of customers of major online retail platforms operating in Tehran, Iran. A sample of 384 online shoppers was selected using stratified convenience sampling. Data were collected through a standardized questionnaire measuring perceptions of dynamic pricing strategies, purchase behavior, customer satisfaction, repurchase intention, and customer trust in the platform using a five-point Likert scale. Content validity was confirmed by academic experts, and reliability indices exceeded acceptable thresholds. Data analysis was conducted using SPSS 27 for preliminary analysis and SmartPLS 4 for measurement and structural model evaluation, including moderation analysis through bootstrapping procedures. The results indicated that big data–driven dynamic pricing strategies had a significant positive effect on purchase behavior, customer satisfaction, and repurchase intention. Purchase behavior and customer satisfaction were found to significantly predict repurchase intention, demonstrating their mediating roles in translating pricing strategies into loyalty outcomes. Furthermore, customer trust in the platform significantly moderated the relationships between dynamic pricing strategies and all dependent variables, strengthening the effects of pricing strategies on behavioral and attitudinal outcomes. The structural model demonstrated strong explanatory power, confirming that trust-enhanced dynamic pricing contributes substantially to customer engagement and retention in online retail environments. The findings demonstrate that dynamic pricing supported by big data analytics represents a strategic mechanism for improving customer behavioral responses and long-term loyalty in online retail platforms. However, the effectiveness of algorithmic pricing depends heavily on customer trust, which amplifies positive consumer perceptions and acceptance of adaptive pricing practices. Integrating technological capability with trust-building strategies is therefore essential for sustainable competitive advantage in digital retail ecosystems.

Keywords: Dynamic Pricing; Big Data Analytics; Customer Trust; Purchase Behavior; Customer Satisfaction; Repurchase Intention; Online Retailing; E-Commerce Analytics.

1. Introduction

The rapid expansion of digital technologies has fundamentally transformed the structure of global retail markets, giving rise to highly data-driven online commerce ecosystems in which pricing decisions, customer interactions, and purchasing processes are increasingly governed by advanced analytics and artificial intelligence. Contemporary e-commerce environments no longer rely on static pricing strategies; instead, retailers employ dynamic pricing mechanisms supported by big data analytics to adjust prices in real time according to demand fluctuations, customer preferences, competitor actions, and contextual market signals. These technological transformations have altered traditional consumer–retailer relationships and created new strategic opportunities for enhancing customer engagement, operational efficiency, and long-term loyalty [1, 2].

The integration of artificial intelligence (AI) and machine learning into online retail platforms enables firms to analyze massive volumes of structured and unstructured data generated through customer browsing behavior, transaction histories, clickstream patterns, and social interactions. Such analytical capabilities allow organizations to personalize pricing and promotional strategies at unprecedented levels of precision. AI-driven systems continuously learn from customer responses, thereby optimizing pricing structures to maximize both firm profitability and perceived customer value [3, 4]. The technical implementation of AI/ML infrastructures within modern e-commerce platforms has therefore become a core competitive capability, shaping how retailers predict demand and manage consumer decision processes [1].

Dynamic pricing supported by big data represents one of the most influential applications of analytics in digital retailing. Machine learning–based price suggestion algorithms analyze historical purchasing patterns, inventory conditions, and market dynamics to recommend optimal pricing strategies that adapt in real time to environmental changes [5]. Research shows that algorithmic pricing systems improve responsiveness to market volatility while enabling retailers to balance revenue optimization with customer experience considerations [6]. As online markets become increasingly competitive, retailers must rely on data-driven pricing to remain agile and sustain customer attention in rapidly evolving digital marketplaces [7, 8].

From a consumer perspective, pricing plays a critical psychological role in shaping purchasing decisions. Online shoppers are highly sensitive to price transparency, perceived fairness, and value comparison across competing platforms. Advanced-data consumer behavior analytics reveal that personalized pricing and recommendation systems significantly influence purchase intention by aligning offers with individual preferences and situational needs [9]. Machine learning models capable of predicting online user purchase intention further demonstrate that pricing cues interact with behavioral signals such as browsing duration, product comparison activities, and promotional exposure to guide decision-making processes [10].

The emergence of real-time analytics has also enabled retailers to move beyond transactional marketing toward predictive customer insight generation. Real-time data streams allow firms to monitor consumer engagement continuously, evaluate responses to pricing changes, and modify marketing strategies instantly. Studies emphasize that real-time analytics strengthens strategic decision-making by transforming raw data into actionable knowledge about customer behavior patterns [6, 11]. Moreover, deep learning–based personalized marketing systems enhance consumer relevance by delivering customized experiences that increase satisfaction and emotional attachment to online platforms [12].

Another critical aspect of contemporary e-commerce environments concerns the role of customer trust. As pricing becomes algorithmically determined, consumers increasingly evaluate whether platforms operate transparently and fairly. Trust in digital platforms has emerged as a central determinant of customer acceptance of automated decision systems. AI-powered trust and security mechanisms, including blockchain verification and machine learning–based fraud detection, significantly enhance confidence in online transactions and reduce perceived risk [13]. Research indicates that perceived online safety directly influences customer satisfaction and willingness to continue purchasing through digital channels [14].

Customer trust becomes particularly important when dynamic pricing strategies are implemented. While personalized pricing can improve efficiency, it may also generate perceptions of price discrimination if consumers believe pricing decisions are opaque or unfair. Therefore, trust functions as a contextual factor that shapes how customers interpret price variability. Studies on consumer experiences in emerging digital markets demonstrate that transparency, reliability, and platform credibility significantly moderate behavioral reactions to online commerce innovations [15, 16]. Without sufficient trust, even technologically sophisticated pricing systems may fail to achieve positive customer outcomes.

Big data analytics also contributes to improved customer segmentation and behavioral modeling. Machine learning segmentation techniques enable retailers to classify customers according to preferences, spending capacity, and engagement patterns, allowing more precise alignment between pricing strategies and consumer expectations [17]. Similarly, regression and predictive modeling approaches enhance sales forecasting accuracy, supporting dynamic pricing optimization based on demand prediction [18]. These developments highlight the growing interdependence between data science capabilities and retail marketing effectiveness.

In addition to pricing optimization, big data technologies facilitate automation of customer feedback analysis and sentiment monitoring. Automated sentiment classification systems analyze reviews, ratings, and user-generated content to identify customer attitudes toward products and pricing policies [19]. Positive online reviews and ratings have been shown to strongly influence consumer purchase behavior by reinforcing perceptions of product quality and platform credibility [20]. Consequently, dynamic pricing must be understood not merely as an economic tool but as part of an integrated customer experience ecosystem.

Technological innovation has also reshaped supply chain operations and inventory management in e-commerce. IoT-based supply chain frameworks supported by machine learning algorithms enable real-time coordination between logistics, warehousing, and pricing decisions, ensuring that prices reflect operational realities such as stock availability and delivery capacity [4]. Neural-network-based prediction systems further enhance retailers' ability to anticipate demand spikes associated with special events or seasonal trends, allowing dynamic adjustment of prices and promotions [21]. These capabilities demonstrate that pricing strategies increasingly depend on interconnected digital infrastructures rather than isolated marketing decisions.

The broader transformation of retail markets driven by digitalization has intensified competition and accelerated innovation cycles. Technological advancements in retail marketing have enhanced personalization, responsiveness, and customer engagement while simultaneously increasing consumer expectations for seamless experiences [2]. Machine learning applications in retail banking and marketing contexts further confirm that data-driven decision systems significantly improve targeting accuracy and customer relationship management effectiveness [22]. Consequently, retailers must integrate analytics-driven pricing with broader digital transformation strategies.

Theoretical perspectives on e-commerce development emphasize that digital business models increasingly rely on data as a strategic resource. In customer-to-customer and platform-based commerce ecosystems, value creation emerges from continuous data exchange between users and platforms, enabling adaptive business model activities that respond dynamically to consumer behavior [23]. The integration of AI systems within retail platforms therefore represents not only a technological innovation but also a fundamental shift toward data-centric value generation.

Dynamic pricing also interacts with operational performance and risk management capabilities. AI-supported decision systems improve operational efficiency by optimizing payment flexibility, logistics coordination, and resource allocation processes, which ultimately enhance overall platform performance [24]. Similarly, algorithmic learning approaches originally developed for bidding and resource allocation environments demonstrate the effectiveness of adaptive learning models in optimizing decision outcomes under uncertainty [25]. These insights reinforce the applicability of intelligent pricing mechanisms within complex online retail environments.

Despite extensive global research on AI-driven retail innovations, empirical evidence concerning the behavioral consequences of big data–based dynamic pricing in emerging e-commerce markets remains limited. Many developing digital economies, including Iran's rapidly growing online retail sector, exhibit unique consumer characteristics shaped by cultural expectations, technological adoption levels, and trust dynamics. Studies examining cross-border and spatial effects of e-commerce activities indicate that regional market structures and retail ecosystems significantly influence customer responses to digital innovations [26]. Therefore, contextualized research is necessary to understand how dynamic pricing operates within specific national environments.

Furthermore, advances in predictive analytics demonstrate that consumer purchase decisions increasingly depend on complex interactions among technological features, psychological perceptions, and platform credibility. AI-enhanced personalization systems in fashion and retail e-commerce illustrate how tailored recommendations and adaptive pricing mechanisms jointly influence consumer satisfaction and engagement outcomes [27]. These developments suggest that pricing strategies must be analyzed within broader experiential frameworks rather than solely economic models.

The growing reliance on big data analytics has also raised important questions regarding ethical data usage, algorithmic transparency, and consumer autonomy. As retailers collect extensive behavioral data, maintaining consumer trust becomes essential for sustaining long-term platform relationships. Research highlights that secure data governance and transparent algorithmic practices significantly strengthen customer confidence and encourage continued participation in digital commerce ecosystems [13]. Hence, trust can be conceptualized as a moderating mechanism linking technological innovation with consumer behavioral outcomes.

Collectively, prior studies demonstrate that big data analytics, artificial intelligence, and machine learning have revolutionized retail pricing, marketing, and customer relationship management. However, limited integrated research simultaneously examines how dynamic pricing strategies influence purchase behavior, customer satisfaction, and repurchase intention while accounting for the moderating role of customer trust in online retail platforms. Addressing this gap is particularly important in rapidly digitalizing retail environments where consumer perceptions of fairness and trust determine the success of algorithmic pricing adoption.

Accordingly, the aim of this study is to examine the impact of big data–driven dynamic pricing strategies on purchase behavior, customer satisfaction, and repurchase intention in Iranian online retail stores, considering the moderating role of customer trust in the platform.

2. Methodology

This study was conducted using an applied research approach with a quantitative methodology and a correlational–causal research design based on structural equation modeling. The purpose of the research was to examine the relationships between big data–driven dynamic pricing strategies and key customer behavioral outcomes, including purchase behavior, customer satisfaction, and repurchase intention, while simultaneously assessing the moderating role of customer trust in online retail platforms. The statistical population consisted of customers of major online retail stores operating in Tehran, Iran, who had recent experience purchasing products through digital retail platforms employing algorithmic or dynamically adjusted pricing mechanisms.

Participants were selected from active users of prominent Iranian online retail platforms such as Digikala, Bamilo-style marketplaces, and other multi-vendor e-commerce websites operating within Tehran. Inclusion criteria required respondents to have completed at least one online purchase during the previous six months and to be familiar with price changes or promotional pricing in online environments. A total of **384 customers from Tehran** were selected as the research sample size based on the Krejcie and Morgan sampling table for large populations. Sampling was conducted using a stratified convenience sampling method to ensure representation across different age groups, gender categories, educational levels, and online shopping frequency patterns. Data collection was carried out digitally through online questionnaires distributed via social media channels, customer communities, and electronic shopping forums commonly used by Tehran-based consumers. Participation was voluntary, anonymous, and conditioned upon informed consent, and respondents were assured that all collected data would be used solely for academic research purposes.

Data were collected using a structured self-report questionnaire developed through the integration of validated measurement scales adapted to the context of Iranian online retailing. The questionnaire consisted of several sections designed to measure the core constructs of the study. The first section captured demographic information, including age, gender, education level, frequency of online purchases, and preferred e-commerce platforms. The second section measured perceptions of big data–driven dynamic pricing strategies, focusing on consumers' awareness of price personalization, real-time price adjustments, perceived fairness of algorithmic pricing, and responsiveness of pricing to demand fluctuations.

Purchase behavior was assessed through items reflecting consumers' actual buying tendencies, responsiveness to price changes, and decision-making speed during online shopping processes. Customer satisfaction was measured using multidimensional indicators evaluating overall shopping experience, perceived value for money, and satisfaction with pricing transparency and platform performance. Repurchase intention was operationalized through items assessing willingness to revisit the platform, likelihood of continued purchasing, and intention to recommend the platform to others. Customer trust in the platform, considered the moderating variable, was measured through dimensions such as perceived reliability, data security, transparency of pricing algorithms, and confidence in platform integrity.

All questionnaire items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. Content validity was confirmed through expert evaluation involving university faculty members specializing in marketing management, digital commerce, and consumer behavior. Construct validity was examined through confirmatory factor analysis prior to hypothesis testing. Reliability of the measurement instrument was evaluated using Cronbach's alpha coefficients and composite reliability indices, all exceeding the acceptable threshold of 0.70, indicating satisfactory internal consistency. A pilot study involving 30 online shoppers from Tehran was conducted to refine wording clarity, response time, and item comprehensibility before full-scale data collection.

Data analysis was performed using a multistage statistical procedure aligned with structural equation modeling methodology. Initially, raw data were screened for missing responses, outliers, and normality assumptions. Descriptive statistics were calculated to summarize demographic characteristics and central tendencies of study variables. Measurement model evaluation was then conducted through confirmatory factor analysis to assess factor loadings, convergent validity, discriminant validity, and overall model adequacy.

Following validation of the measurement model, the structural model was estimated to test hypothesized relationships among dynamic pricing strategies, purchase behavior, customer satisfaction, and repurchase intention. The moderating effect of customer trust in the platform was examined using interaction modeling within the structural equation framework. Model fit was evaluated using standard goodness-of-fit indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

All statistical analyses were conducted using SPSS version 27 for preliminary analysis and SmartPLS version 4 for structural equation modeling and moderation testing. Bootstrapping procedures with 5,000 resamples were employed to determine the significance of path coefficients and indirect effects. The analytical process enabled simultaneous examination of direct, indirect, and moderating relationships, providing a comprehensive understanding of how big data–driven dynamic pricing strategies influence customer behavioral outcomes within Iranian online retail environments.

3. Findings and Results

The demographic analysis showed that 54.4% of respondents were male and 45.6% were female, indicating relatively balanced gender participation among online shoppers. In terms of age distribution, 28.1% of participants were between 18 and 25 years old, 41.7% were between 26 and 35 years old, 21.6% were between 36 and 45 years old, and 8.6% were older than 45 years. Educational background revealed that 18.2% held a diploma or associate degree, 52.6% possessed a bachelor's degree, and 29.2% had postgraduate education. Regarding online shopping frequency, 33.9% reported purchasing online at least once per month, 46.6% indicated two to four purchases monthly, and 19.5% reported frequent weekly purchases. These statistics confirm that the respondents represented active digital consumers familiar with pricing fluctuations and online purchasing environments, thereby supporting the appropriateness of the selected sample for investigating dynamic dynamic pricing mechanisms.

Table 1. Measurement Model Evaluation (Factor Loadings, Reliability, and Validity)

Construct	Indicator	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Dynamic Pricing Strategies	DPS1	0.812	0.901	0.921	0.661
	DPS2	0.846			
	DPS3	0.834			
	DPS4	0.793			
Purchase Behavior	PB1	0.801	0.884	0.909	0.627
	PB2	0.817			
	PB3	0.772			
Customer Satisfaction	CS1	0.869	0.912	0.931	0.694
	CS2	0.841			
	CS3	0.823			
Repurchase Intention	RI1	0.878	0.918	0.937	0.713
	RI2	0.852			
	RI3	0.824			
Customer Trust	CT1	0.836	0.905	0.924	0.671
	CT2	0.814			
	CT3	0.828			

The results presented in Table 1 indicate strong psychometric properties of the measurement model. All factor loadings exceeded the recommended threshold of 0.70, demonstrating adequate indicator reliability. Cronbach's alpha and composite reliability values for all constructs were above 0.80, confirming high internal consistency reliability. The Average Variance Extracted (AVE) values were higher than 0.50 for all constructs, indicating satisfactory convergent validity. These findings confirm that the measurement instruments reliably captured perceptions of dynamic pricing strategies, purchase behavior, customer satisfaction, repurchase intention, and customer trust in online retail platforms.

Table 2. Discriminant Validity Assessment (Fornell–Larcker Criterion)

Construct	DPS	PB	CS	RI	CT
Dynamic Pricing Strategies (DPS)	0.813				
Purchase Behavior (PB)	0.564	0.792			
Customer Satisfaction (CS)	0.618	0.602	0.833		
Repurchase Intention (RI)	0.641	0.587	0.706	0.845	
Customer Trust (CT)	0.532	0.551	0.623	0.688	0.819

Table 2 demonstrates discriminant validity among latent constructs using the Fornell–Larcker criterion. The square root of AVE values shown along the diagonal exceeded inter-construct correlations in all cases. This result confirms that each construct captured a distinct conceptual domain and that overlap among variables remained within acceptable limits. Therefore, dynamic pricing perceptions, behavioral responses, satisfaction outcomes, repurchase intention, and trust represent empirically separable constructs within the structural model.

Table 3. Structural Model Path Coefficients and Hypothesis Testing

Hypothesized Path	Path Coefficient (β)	t-value	p-value	Result
Dynamic Pricing → Purchase Behavior	0.472	9.384	<0.001	Supported
Dynamic Pricing → Customer Satisfaction	0.521	10.126	<0.001	Supported
Dynamic Pricing → Repurchase Intention	0.298	5.614	<0.001	Supported
Purchase Behavior → Repurchase Intention	0.267	4.921	<0.001	Supported
Customer Satisfaction → Repurchase Intention	0.401	7.885	<0.001	Supported

The structural model results reported in Table 3 indicate that big data–driven dynamic pricing strategies significantly influenced all key outcome variables. Dynamic pricing exerted a strong positive effect on purchase behavior ($\beta = 0.472$), suggesting that adaptive pricing mechanisms encourage consumers to make faster and more frequent purchasing decisions. A stronger relationship emerged between dynamic pricing and customer satisfaction ($\beta = 0.521$), indicating that personalized and responsive pricing enhances perceived value and overall shopping experience. The direct effect on repurchase intention was also significant, although partially mediated through behavioral and satisfaction pathways. Both purchase behavior and customer satisfaction significantly predicted repurchase intention, demonstrating that satisfied consumers who respond positively to pricing dynamics are more likely to continue engaging with online retail platforms.

Table 4. Moderating Effect of Customer Trust in the Platform

Interaction Effect	β	t-value	p-value	Effect
Dynamic Pricing × Customer Trust → Purchase Behavior	0.186	3.742	<0.001	Significant
Dynamic Pricing × Customer Trust → Customer Satisfaction	0.214	4.168	<0.001	Significant
Dynamic Pricing × Customer Trust → Repurchase Intention	0.231	4.523	<0.001	Significant

Table 4 presents moderation analysis results examining whether customer trust strengthens the impact of dynamic pricing strategies. The interaction terms were statistically significant across all dependent variables. Higher levels of platform trust amplified the positive effects of dynamic pricing on purchase behavior, satisfaction, and repurchase intention. These findings indicate that algorithmic pricing alone is insufficient to generate favorable consumer responses unless accompanied by perceived reliability, transparency, and trustworthiness of the online platform.

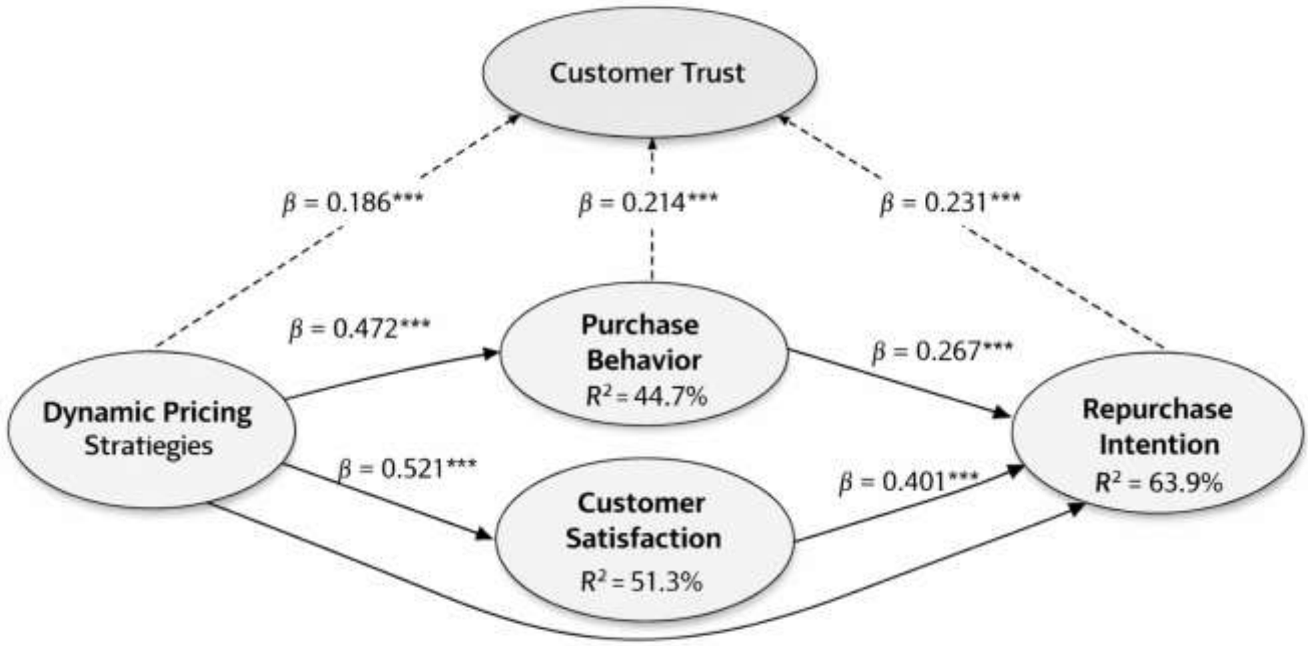

Figure 1. Structural Model of the Effects of Big Data–Driven Dynamic Pricing Strategies on Customer Outcomes with the Moderating Role of Platform Trust

The structural model illustrates standardized path coefficients among constructs and confirms overall model adequacy. The model explained 44.7% of variance in purchase behavior, 51.3% of variance in customer satisfaction, and 63.9% of variance in repurchase intention. These values demonstrate substantial explanatory power of dynamic pricing strategies combined with customer trust. The figure highlights that customer satisfaction emerged as the strongest predictor of repurchase intention, while customer trust functioned as a reinforcing contextual mechanism that intensified consumer responsiveness to dynamic pricing practices. Collectively, the findings suggest that big data analytics enables retailers to influence not only transactional outcomes but also relational loyalty processes within Iranian online retail ecosystems.

4. Discussion and Conclusion

The present study aimed to investigate the impact of big data–driven dynamic pricing strategies on purchase behavior, customer satisfaction, and repurchase intention in Iranian online retail stores while examining the moderating role of customer trust in the platform. The findings provide strong empirical evidence that dynamic pricing supported by big data analytics plays a central role in shaping consumer responses in digital retail environments. Overall, the results confirm that technologically enabled pricing mechanisms influence not only immediate purchasing decisions but also long-term relational outcomes such as satisfaction and loyalty intentions.

The first major finding demonstrated that dynamic pricing strategies significantly and positively affected customer purchase behavior. This result suggests that real-time pricing adjustments supported by big data analytics successfully stimulate consumer engagement and accelerate purchase decisions. Dynamic pricing reduces decision uncertainty by aligning prices with perceived market conditions, promotional timing, and consumer expectations. This finding aligns with research emphasizing that AI-driven pricing systems enhance responsiveness to consumer demand and enable retailers to optimize transaction outcomes through continuous learning processes [1, 5]. Studies on consumer behavior analytics similarly show that advanced data techniques allow firms to anticipate user intentions and influence purchasing behavior by delivering context-sensitive offers [9, 10].

Furthermore, the positive relationship between dynamic pricing and purchase behavior reflects the growing role of real-time data analytics in retail decision-making. Prior research highlights that data-driven insight generation enables retailers to transform customer behavioral signals into actionable pricing strategies that encourage immediate purchase responses [6, 11]. The results therefore support the theoretical perspective that big data analytics functions as a behavioral trigger mechanism within online commerce ecosystems.

The study also revealed that dynamic pricing strategies significantly improved customer satisfaction. This finding indicates that consumers perceive adaptive pricing as beneficial when it enhances perceived fairness, value, and personalization. Rather than viewing price changes negatively, customers appear to interpret algorithmic pricing as evidence of technological sophistication and customer orientation when transparency and usability are maintained. This outcome is consistent with studies demonstrating that AI-powered personalization improves customer experience by tailoring services and offerings to individual needs [3, 27].

Research on technological innovation in retail marketing further explains that digital transformation enhances satisfaction by creating seamless shopping journeys characterized by convenience, relevance, and responsiveness [2]. Machine learning–supported marketing systems increase engagement by reducing search effort and improving product–price matching, which contributes directly to customer satisfaction outcomes [22]. Additionally, automated sentiment analysis and feedback systems help retailers continuously refine customer experiences, reinforcing satisfaction through responsive platform adaptation [19]. The present findings therefore reinforce the argument that pricing strategy effectiveness depends not only on economic efficiency but also on experiential value creation.

Another important result showed that dynamic pricing exerted a direct positive effect on repurchase intention. This finding highlights that adaptive pricing contributes to customer loyalty formation when supported by data intelligence. Repurchase intention reflects consumers' confidence that future interactions with the platform will provide favorable outcomes. Previous research demonstrates that predictive analytics and machine learning enable retailers to maintain long-term relationships by anticipating customer needs and delivering personalized experiences over time [17, 26].

The results further revealed that purchase behavior and customer satisfaction significantly predicted repurchase intention, confirming their mediating roles in transforming pricing strategies into loyalty outcomes. These findings correspond with e-commerce studies showing that positive transactional experiences and emotional satisfaction jointly shape consumers' willingness to revisit digital platforms [7, 8]. Positive online evaluations and reviews reinforce customer confidence and encourage continued purchasing behavior, strengthening the cycle of platform loyalty [20]. Consequently, repurchase intention emerges as a cumulative outcome of behavioral engagement and experiential satisfaction driven by dynamic pricing practices.

A central contribution of the study concerns the moderating role of customer trust in the platform. The findings demonstrated that trust significantly strengthened the effects of dynamic pricing on purchase behavior, satisfaction, and repurchase intention. This result confirms that technological innovation alone does not guarantee positive consumer reactions; rather, customer trust determines whether algorithmic pricing is interpreted as beneficial or exploitative. Trust reduces perceived risk associated with automated pricing decisions and enhances acceptance of price variability.

These results strongly align with research emphasizing the importance of secure and trustworthy digital infrastructures in e-commerce environments. AI-powered trust and security systems increase consumer confidence by ensuring data protection and transaction reliability [13]. Similarly, studies linking online safety to marketing effectiveness indicate that consumer confidence enhances engagement with digital services and strengthens long-term customer relationships [14]. The moderating effect observed in this study confirms that trust operates as a psychological lens through which consumers evaluate data-driven pricing mechanisms.

The findings also resonate with broader discussions of digital business model transformation. In platform-based commerce ecosystems, value creation increasingly depends on sustained user trust and data exchange between customers and platforms [23]. When customers trust a platform, they are more willing to share behavioral data, which further improves algorithmic accuracy and strengthens pricing optimization processes. Thus, trust and big data analytics form a mutually reinforcing cycle supporting both operational efficiency and customer loyalty.

From an operational perspective, the results demonstrate how dynamic pricing integrates with supply chain intelligence and predictive analytics. IoT-based logistics systems and machine learning forecasting models allow prices to reflect real-time inventory and operational conditions, thereby improving customer satisfaction and perceived reliability [4, 21]. Adaptive decision-making systems originally developed for complex optimization environments also confirm the effectiveness of learning-based pricing under uncertainty [25]. These findings suggest that dynamic pricing represents a strategic capability linking marketing, operations, and analytics functions within digital retail organizations.

The study additionally contributes to understanding emerging-market e-commerce behavior. Consumer experiences in developing digital economies differ from mature markets due to varying levels of technological familiarity, institutional trust, and platform maturity. Research on social commerce adoption shows that consumer experiences in emerging markets are strongly influenced by trust perceptions and social validation mechanisms [15]. The present results confirm that trust plays an especially critical role in such contexts, reinforcing the necessity of transparent pricing communication and reliable platform governance.

Overall, the findings support a comprehensive theoretical framework in which big data analytics enables dynamic pricing, dynamic pricing shapes behavioral and experiential outcomes, and customer trust amplifies these relationships. The study therefore integrates technological, behavioral, and relational perspectives into a unified explanation of customer responses in online retail environments.

Despite its contributions, this study has several limitations that should be acknowledged. First, data were collected exclusively from customers located in Tehran, which may limit generalizability to other geographic regions with different socio-economic or technological conditions. Consumer attitudes toward dynamic pricing may vary across cities or rural areas where digital literacy and online shopping adoption differ. Second, the research relied on self-reported questionnaire data, which may introduce response bias or social desirability effects. Although statistical procedures were employed to ensure reliability and validity, behavioral intentions may not fully represent actual purchasing behavior. Third, the cross-sectional research design restricts the ability to establish causal relationships over time. Consumer perceptions of pricing strategies and trust may evolve as technological familiarity increases, suggesting the need for longitudinal investigation.

Future studies may expand the research scope by conducting comparative analyses across different countries or cultural environments to examine whether dynamic pricing effectiveness varies according to institutional trust and digital maturity levels. Longitudinal research designs could provide deeper insight into how customer trust develops over repeated interactions with algorithmic pricing systems. Researchers may also investigate additional moderating variables such as perceived price fairness, privacy concerns, technological anxiety, or platform transparency. Incorporating behavioral tracking data rather than self-reported measures could enhance measurement precision. Moreover, future research may explore sector-specific applications of dynamic pricing, including fashion retail, travel services, digital marketplaces, and subscription-based platforms, to better understand industry-level differences.

Online retail managers should invest in advanced big data analytics capabilities to implement dynamic pricing strategies that respond intelligently to consumer behavior and market conditions. However, technological adoption must be accompanied by transparent communication regarding pricing mechanisms to strengthen customer trust. Platforms should prioritize data security, clear pricing explanations, and consistent customer service to ensure positive interpretations of price variability. Retailers are encouraged to integrate pricing analytics with customer experience management systems so that personalization enhances satisfaction rather than creating perceptions of unfairness. Training marketing and analytics teams to collaborate closely can help organizations balance profitability objectives with long-term relationship building. Finally, policymakers and platform designers should develop ethical guidelines for algorithmic pricing to ensure sustainable and trust-based digital commerce ecosystems.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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References

[1] P. S. Pelluru, "Technical Implementation of AI/ML Systems in Modern eCommerce: A Deep Dive," *European Journal of Computer Science and Information Technology,* vol. 13, no. 6, pp. 63-77, 2025, doi: 10.37745/ejcsit.2013/vol13n66377.

[2] G. Wilson, W. L. Brown, and O. Johnson, "Technological Innovations and Their Effect on Retail Marketing Effectiveness," 2024, doi: 10.20944/preprints202407.1154.v1.

[3] M. Johnpaul, R. S. B. Miryala, M. Mazurek, G. Jayaprakashnarayana, and R. K. Miryala, "Artificial Intelligence and Machine Learning in eCommerce," pp. 31-58, 2024, doi: 10.4018/979-8-3693-5718-7.ch002.

[4] W. Wang, "A IoT-Based Framework for Cross-Border E-Commerce Supply Chain Using Machine Learning and Optimization," *Ieee Access,* vol. 12, pp. 1852-1864, 2024, doi: 10.1109/access.2023.3347452.

[5] L. N. T. Quang, U. N. T. Thao, A. D. V. Nhi, and H. N. T. Phuong, "E-Commerce Price Suggestion Algorithm – A Machine Learning Application," pp. 2598-2609, 2022, doi: 10.46254/in02.20220609.

[6] M. A. Raji, H. B. Olodo, T. T. Oke, W. A. Addy, O. C. Ofodile, and A. T. Oyewole, "Real-Time Data Analytics in Retail: A Review of USA and Global Practices," *GSC Advanced Research and Reviews,* vol. 18, no. 3, pp. 059-065, 2024, doi: 10.30574/gscarr.2024.18.3.0089.

[7] A. Tripathi and A. Shukla, "A Review on Impact of E-Commerce on Retailers," *Adhyayan a Journal of Management Sciences,* vol. 14, no. 02, pp. 1-3, 2024, doi: 10.21567/adhyayan.v14i2.01.

[8] Z. Zhu, "Future Development Trend of UK Retail Industry," pp. 1823-1830, 2022, doi: 10.2991/978-2-494069-31-2_213.

[9] N. J. Sapara and H. H. Patel, "Consumer Behavior Analysis Through Advanced-Data Techniques: A Review for Utilities in Retail Marketing," *Interantional Journal of Scientific Research in Engineering and Management,* vol. 08, no. 10, pp. 1-5, 2024, doi: 10.55041/ijsrem37895.

[10] A. Kumar, D. K. M, V. D. J. Macedo, B. R. Mohan, and A. P. N, "Machine Learning Approach for Prediction of the Online User Intention for a Product Purchase," *International Journal on Recent and Innovation Trends in Computing and Communication,* vol. 11, no. 1s, pp. 43-51, 2023, doi: 10.17762/ijritcc.v11i1s.5992.

[11] O. R. Amosu *et al.*, "Data-Driven Personalized Marketing: Deep Learning in Retail and E-Commerce," *World Journal of Advanced Research and Reviews,* vol. 23, no. 2, pp. 788-796, 2024, doi: 10.30574/wjarr.2024.23.2.2395.

[12] O. R. Amosu, P. Kumar, A. Fadina, Y. M. Ogunsuji, S. Oni, and K. Adetula, "Harnessing Real-Time Data Analytics for Strategic Customer Insights in E-Commerce and Retail," *World Journal of Advanced Research and Reviews,* vol. 23, no. 2, pp. 880-889, 2024, doi: 10.30574/wjarr.2024.23.2.2407.

[13] N. Ahmed, M. E. Hossain, Z. Hossain, M. M. J. Kabir, and I. Hossain, "AIPowered Trust and Security: Enhancing ECommerce With Blockchain and Machine Learning," *Formosa Journal of Science and Technology,* vol. 4, no. 1, pp. 413-430, 2025, doi: 10.55927/fjst.v4i1.13680.

[14] Y. I. Lee and P. R. Trim, "Enhancing Marketing Provision Through Increased Online Safety That Imbues Consumer Confidence: Coupling AI and ML With the AIDA Model," *Big Data and Cognitive Computing,* vol. 6, no. 3, p. 78, 2022, doi: 10.3390/bdcc6030078.

[15] A. A. A. Jamil and A. A. Ismail, "The Use of 'Ecommerce' and 'Social Commerce in Emerging Markets': Omani Female Millennials' Experiences," *Information Development,* vol. 40, no. 3, pp. 461-477, 2022, doi: 10.1177/02666669221145411.

[16] P. Venter and R. G. Duffett, "A Framework for a Generic Retail Charter: A Guide Towards Sustainability and Stakeholder Support," *Sustainability,* vol. 14, no. 23, p. 15848, 2022, doi: 10.3390/su142315848.

[17] J. George and R. Sona, "Leveraging Machine Learning for Customer Segmentation in Retail," *Interantional Journal of Scientific Research in Engineering and Management,* vol. 08, no. 03, pp. 1-9, 2024, doi: 10.55041/ijsrem29102.

[18] M. S. B. Ilyas, A. Ikram, M. A. Butt, and I. Tariq, "Comparative Analysis of Regression Algorithms Used to Predict the Sales of Big Marts," *Jicet,* vol. 3, no. 1, 2023, doi: 10.56536/jicet.v3i1.53.

[19] V. P. Sakthivel, G. V. Varshini, M. NethraSai, D. Rajashekar, V. K. Kaliappan, and J. Li, "Customer Feedback Automation and Classification Using Sentiment Analysis, Robotic Process Automation and Uipath," pp. 899-907, 2023, doi: 10.13052/rp-9788770040723.175.

[20] H. Diyora, "The Influence of Positive Online Reviews and Rating on Consumer Behavior," *Advances in Science and Sustainability,* vol. 1, no. 12, pp. 9-13, 2025, doi: 10.70728/susta.v01.i11.003.

[21] T. Alwis and P. Pemarathna, "Special Event Item Prediction System for Retails – Using Neural Network Approach," pp. 313-322, 2022, doi: 10.54389/bbly6340.

[22] Y. Wu, "Machine Learning Approaches for Retail Bank Marketing Practice," *BCP Business & Management,* vol. 23, pp. 931-937, 2022, doi: 10.54691/bcpbm.v23i.1475.

[23] H. Hokkanen, "Business Model Activities in C2C eCommerce," *Journal of Business Models,* vol. 13, no. 1, pp. 119-145, 2025, doi: 10.54337/jobm.v13i1.7624.

[24] M. T. Hejazi, O. Alrusaini, and H. Beyari, "The Effect of Artificial Intelligence and Payment Flexibility on Operational Performance: The Enabling Role of Supply Chain Risk Management," *Uncertain Supply Chain Management,* vol. 10, no. 4, pp. 1117-1130, 2022, doi: 10.5267/j.uscm.2022.8.015.

[25] Y. Xie *et al.*, "Simulation of the Bidding Behavior of Electricity Retailers Based on the <i>Q</I>-Learning Algorithm," *Wireless Communications and Mobile Computing,* vol. 2022, no. 1, 2022, doi: 10.1155/2022/8007634.

[26] X. Pan, G. Li, M. Dresner, and B. Mantin, "Exploring the Impacts of Ecommerce Activities on the Spatial Resilience of Warehouse Clubs: The role of Retail Agglomeration," *International Journal of Physical Distribution & Logistics Management*, vol. 54, no. 4, pp. 392-417, 2024, doi: 10.1108/ijpdlm-12-2022-0365.

[27] K. Agrawal, "AI-enhanced Intelligent Fashion eCommerce: Virtual Try-on and Personalized Style Recommendations in Action," *World Journal of Advanced Engineering Technology and Sciences*, vol. 15, no. 1, pp. 2142-2150, 2025, doi: 10.30574/wjaets.2025.15.1.0475.