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Artificial Intelligence in Pricing: A Game-Changer for Business Success

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Abstract: *This paper investigates the game-changing potential of artificial intelligence (AI) in transforming pricing strategies across various industries. The research begins by defining general AI and its key components, such as machine learning, natural language processing, and computer vision. The paper then explores the application of AI in pricing, discussing how these technologies can be leveraged to optimize demand forecasting, personalization, and dynamic pricing. The benefits of incorporating AI in pricing, including increased accuracy, efficiency, and customer satisfaction, are highlighted. However, the discussion investigates challenges associated with implementing AI in pricing, such as data quality, ethical considerations, and regulatory compliance. Future research directions are proposed, including the integration of AI with other advanced analytics techniques and the development of novel pricing models enabled by AI. In conclusion, this paper underscores the disruptive impact of AI on pricing strategies and emphasizes the need for businesses to embrace this technology to stay competitive and achieve long-term success.*

1. INTRODUCTION

Artificial Intelligence (AI) is a transformative technology that significantly impacts global economic sectors through core components like machine learning, natural language processing, and computer vision. These AI systems, which include applications such as virtual assistants, bots, and predictive analytics, are increasingly utilized for marketing and data analysis, enhancing decision-making and operational efficiency.

The systems, based on AI significantly reduce uncertainty and enhance predictability, which in turn lowers the risk discount that typically depresses prices, especially for early-stage innovations. Agrawal et al. (2018, 2022) describe AI as a tool that makes predictions cheap and scalable, enabling decision-making to shift from rules-based to outcome-based processes. As AI improves prediction accuracy, it will transform pricing by enabling outcome-based models, optimizing value delivery at lower costs, and fostering collaboration to maximize value for all parties involved rather than relying on traditional price optimization methods based on willingness to pay.

In a KPMG (2023) survey from March, 65% of 225 executives indicated that Generative AI will have a high or extremely high impact on their organizations. The rapid adoption of AI in 2023, fueled by decreasing computing costs and accessible internet-based training data, has shifted it from a niche technology to a widespread tool. Executives see Generative AI as particularly promising for driving innovation (78%), technology investment (74%), and customer success (73%), highlighting its transformative potential across various business functions, such as optimizing pricing to maximize revenue and customer retention.

Artificial intelligence has become a pivotal focus in both academic discourse and business practices, with Dwivedi et al. (2024) emphasizing the imperative of delineating stakeholder benefits and quantifiable

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metrics of AI's impact, while synchronizing research endeavors with pragmatic applications, and Agarwal et al. (2024) further advocating for the prioritization of AI use cases based on critical multidimensional criteria. Price management in the digital landscape is increasingly reliant on technology and driven by data, with pricing decisions being either fully or partially determined by algorithmic systems (Klein, 2021). In this setting, Artificial Intelligence (AI) is progressively employed for tasks such as sales forecasting, price prediction, and revenue optimization.

According to Kotler (2024), the strategic deployment of AI in marketing decision-making will be pivotal for corporate success in the future. Studies by Hagendorff et al. (2023) and Jansen et al. (2023) illustrate how AI surpasses conventional problem-solving methods in specific scenarios, indicating its capacity to optimize decision-making processes.

2. LITERATURE REVIEW

The integration of technology and data to generate value and monetize marketing efforts has been accelerated by the adoption of artificial intelligence, particularly through the use of pre-trained, large-scale language models with diverse applications (Rossi et al., 2024). The growing significance of big data analytics as a source of competitive advantage has led researchers to provide recommendations for SMEs on leveraging big data (Sanchez-Hughet et al., 2022) and prioritizing its applications (Agarwal et al., 2024). Although numerous AI solutions have been proposed (Agrawal et al., 2022), few studies provide a structured framework for implementing AI in marketing decisions (Wu & Monfort, 2022). Moreover, to the best of our knowledge, there is a lack of comparative evaluations of current AI applications for specific use cases in price management. Various classification criteria for AI systems—such as AI type, industry application, human-AI collaboration modes, and AI's primary function—have been used to assess which configurations show greater user adoption potential (Kelly et al., 2023; Cabrera-Sánchez et al., 2021; Li et al., 2022; Kim et al., 2021). However, there is limited guidance available for decision-making regarding investments in these new technologies, particularly for small and medium-sized enterprises (SMEs), where leaders might be unaware of the ethical concerns surrounding hybrid human-AI decision-making systems (Sanchez-Hughet et al., 2022; Feuerriegel et al., 2022). Despite limited research on the criteria that encourage managers to integrate AI into marketing processes, much insight can be gained from the evolving understanding of consumer behavior towards AI. From the consumer's perspective, AI adoption is frequently examined through technology acceptance models, which highlight key factors influencing people's intent to engage with AI (Kelly et al., 2023; Cabrera-Sánchez et al., 2021; Gursoy et al., 2019). Functional AI systems, in particular, are viewed positively (Kim et al., 2021), and users tend to favor collaborative, interdependent interactions with AI to achieve their objectives (Li et al., 2022). The behavioral drivers identified can generally be categorized into economic cost-benefit analyses and social factors. However, to date, no explicit studies have addressed these criteria in management processes involving human-AI collaboration.

Studies have shown that technological innovation is strongly linked to improved business performance and the long-term viability of SMEs (Rahman & Gogate, 2016). However, only a small proportion of SMEs report actively utilizing AI and incorporating these technologies into their business models (Stentoft et al., 2021). The Massachusetts Institute of Technology and the BCG Henderson Institute survey revealed that enterprises with annual revenues exceeding $10 billion that implemented AI-driven pricing transformations experienced revenue enhancements exceeding $100 million 70% more frequently than those concentrating on alternative domains. Additionally, these companies faced significantly lower failure rates, with only 13% of AI-driven pricing initiatives yielding no benefits, in contrast to 34% of firms whose AI efforts did not target pricing optimization (Hazan et al., 2021).

From an economic and management standpoint, the implementation of AI generally enhances a firm's value proposition by enabling customization, value co-creation, search optimization, and process optimization (Moreno-Izquierdo et al., 2018). This, in turn, improves customer value, both from the perspective of the customer experience and the firm's understanding of customer value. Brown and MacKay (2021) provide strong empirical evidence showing that using pricing algorithms significantly affects pricing trends. They also offer a theoretical analysis suggesting that by relying on these algorithms, companies can adhere to pricing strategies that result in higher prices than they might achieve otherwise.

Miklos-Thal and Tucker (2019) develop a theoretical model showing that algorithms improve firms' ability to predict demand. They suggest that this enhanced forecasting capability may cause firms to break away from collusive behavior more often, resulting in lower prices and greater consumer benefits. Similar arguments can be found in the works of O'Connor and Wilson (2019) and Martin and Rasch (2022).

In response to McKinsey's advocacy for prioritizing AI applications in finance (Agarwal et al., 2024), Erdmann et al. (2024) emphasize the importance of a comprehensive evaluation of AI use cases in pricing—a domain at the intersection of marketing and finance. This integrative approach ensures a thorough understanding of the multifaceted impacts of AI technologies. It enables SMEs to prioritize AI applications effectively, considering not only their economic advantages but also addressing ethical and regulatory factors.

Table 1 illustrates the growing focus on employing AI for task or process automation and enhancement in marketing and finance, particularly for specific functions (AI point solutions). The complexity inherent in decision-making and the deployment of disruptive technologies has been addressed in various contexts using multivariate decision models. The methodological innovation here lies in applying these approaches to AI-driven price setting, a critical element of the Marketing Mix, encompassing all pricing-related tasks where AI solutions have been documented in the literature. This application provides strategic guidance for SMEs on AI investment in pricing, aligning with both immediate operational needs and broader stakeholder requirements.

Table 1. Research contribution embedded in the literature

Authors	**AI in marketing**	**AI in finance**	**AI in process/ task**	**Pricing automation with AI**
Liu (2024); Jafari et al. (2020)		+	+	
Kelly et al. (2023); Gursoy et al. (2019); Brown and MacKay (2021)	+			
Agrawal et al. (2022); Kim et al. (2021); Sanchez-Hughet et al. (2022); Cabrera-Sánchez et al. (2021); Kotler (2024); Miklos-Thal and Tucker (2019); O'Connor and Wilson (2019); Martin and Rasch (2022)	+		+	
Wachter and Mittelstadt (2019); Omoumi et al. (2021); Li et al. (2022); Feuerriegel et al. (2022)			+	
Gerlick and Liozu (2020); Moreno-Izquierdo et al. (2018)	+		+	+
Xu and Zhang (2022); Wu and Monfort (2022)	+			+
Erdmann et al. (2024); Agarwal et al. (2024)	+	+		+
Ferreira et al. (2021); Ambukege et al. (2017)		+	+	+

Source: Adapted from Erdmann et al. (2024)

3. AI-BASED PRICING MODELS

Hedonic pricing theory has historically provided a framework for analyzing price functions as bundles of various attributes and their interrelations (Lancaster, 1966; Rosen, 1974). The integration of AI algorithms into price functions, by leveraging empirical data to identify patterns rather than using a predetermined linear approach, represents a shift from traditional methods while still relying on similar input elements. Comparative studies show that AI-based approaches offer improved accuracy in value forecasting and reduced price prediction errors compared to traditional hedonic pricing methods, though they often trade off interpretability due to the opaque nature of many AI algorithms (Sakri & Ali, 2022; Moreno-Izquierdo et al., 2018; Liu et al., 2018).

The primary applications of AI-enhanced pricing can be classified into two main categories: (1) forecasting tools, which utilize AI-driven price prediction models applicable to various domains such as financial markets, auction environments, energy markets, procurement, exchange rates, or consumer price indices; and (2) price optimization tools, which involve AI-based pricing strategies that adapt to market conditions, including use cases such as personalized pricing, market segmentation, and dynamic pricing (Erdmann et al., 2024).

3.1. AI-Based Price Forecasting Use Cases

AI algorithms, including machine learning and deep learning techniques, are increasingly utilized for predicting stock market prices. Ferreira et al. (2021) highlight the shift from conventional forecasting methods to sophisticated AI models capable of handling large data sets and achieving notable financial gains through advanced data analysis and pattern recognition, underscoring AI's pivotal role in financial decision-making. Similarly, AI has proven effective in forecasting auction prices, with techniques such as genetic algorithms, artificial neural networks, and regression analysis significantly improving the accuracy of real estate auction price predictions, as demonstrated by Kang et al. (2020). The complex and volatile nature of electricity markets also benefits from AI-based forecasting models, which provide precise day-ahead price predictions, as shown by Zaroni et al. (2020). Additionally, AI models enhance the accuracy of procurement price forecasts for agricultural products, by utilizing daily time-series data, offering substantial commercial advantages in optimizing procurement strategies (Jafari et al., 2020). The application of AI models has the potential to substantially improve international price setting, as evidenced by Chen and Hu (2019), who analyze the exchange rate pass-through (ERPT) effect on Chinese export price indices. Their research demonstrates AI's superior forecasting capabilities, facilitating more precise and informed decision-making for stakeholders navigating the intricacies of global trade and economic systems. Advancements in AI have significantly enhanced the forecasting of the Consumer Price Index (CPI), as demonstrated by Ambukege et al. (2017), who utilize neural networks and fuzzy logic to develop a sophisticated machine learning model that leverages data from the Tanzania National Bureau of Statistics. This development underscores AI's effectiveness in improving economic forecasting and decision-making processes, providing a powerful tool for strategic planning across multiple economic domains, a finding similarly observed in AI-based house price index predictions (Xu & Zhang, 2022).

3.2. AI-Based Price Optimization Use Cases

Personalized pricing, as explored by Gerlick and Liozu (2020), underscores the crucial role of AI and algorithmic decision-making in tailoring price settings to individual consumer behaviors and preferences. AI-driven personalized pricing enables the analysis of extensive consumer data sets, facilitating dynamic, real-time price adjustments that enhance the shopping experience by aligning prices with each consumer's perceived value. Gautier et al. (2020) further examine the technological, economic, and legal implications of AI in personalized pricing, focusing on issues such as algorithmic price discrimination and implicit collusion. The utilization of AI to process large volumes of personal data allows for more precise price differentiation, thereby improving the effectiveness of personalized pricing strategies. However, this also raises initial concerns about the need for regulatory oversight in this domain.

Dynamic pricing within the tourism sector as an example, particularly for Airbnb listings as investigated by Moreno-Izquierdo et al. (2018), is markedly improved by AI, especially through the application of machine learning models. The study reveals that AI's ability to analyze large datasets facilitates the optimization of pricing strategies, enabling real-time price adjustments based on market demand, thereby enhancing competitiveness and profitability through advanced pattern recognition and data analytics techniques. Gerlick and Liozu (2020) highlight that organizations in the U.S. and globally are increasingly leveraging AI-driven dynamic pricing as a strategic tool to adapt prices based on competition, market demand, and other influencing factors. This approach has gained significant traction due to its potential to enhance revenue and foster stronger customer engagement. However, companies must address the ethical challenges associated with dynamic pricing, as it can be perceived as discriminatory or unfair to certain customer groups, necessitating a commitment to transparency and ethical standards in its application. Kinoti (2023) explains that dynamic pricing is a flexible strategy that adjusts prices based on factors like time, demand, and market conditions, allowing companies to update prices in real-time. Unlike static pricing, which remains fixed over extended periods, AI-driven dynamic pricing leverages complex algorithms and data analysis to optimize pricing for competitiveness and revenue, enabling swift responses to market fluctuations.

AI techniques for dynamic pricing in Demand-Side Management (DSM) leverage a combination of machine learning (ML), optimization, and deep learning approaches. Supervised learning methods, such as regression and classification models, are frequently employed to analyze historical consumption data and predict future demand trends. Algorithms like decision trees, random forests, and support vector machines can forecast high-demand periods and recommend optimal pricing strategies to encourage load balancing and demand response.

Optimization techniques like genetic algorithms, linear programming, and integer programming play a crucial role in determining the most effective pricing strategies by optimizing resources and maintaining system stability. These methods help utilities design dynamic pricing systems that minimize costs while ensuring grid stability.

Deep learning approaches, such as neural networks, enhance the modeling of complex relationships between factors influencing demand, providing more accurate predictions of future consumption patterns. These algorithms can identify non-linear relationships and subtle patterns that traditional models may miss, improving dynamic pricing decisions (Jha et al., 2024).

These AI-driven pricing mechanisms hold significant promise for enhancing accuracy while minimizing costs and accelerating price adjustments and promotional strategies. By aligning with customer value perceptions and adapting to fluctuating market conditions, these technologies facilitate superior decision-making and confer a competitive edge.

4. ADOPTION OF AI-BASED PRICING

Retailers are navigating a complex pricing landscape due to persistent cost inflation, supply chain disruptions, evolving consumer behaviors, and intensifying price competition. Traditional pricing methods are inadequate, prompting the adoption of AI-powered solutions and dynamic pricing models. Leveraging these advanced tools can enhance gross profits by 5% to 10% and support sustainable revenue growth and improve customer value perception (Boston Consulting Group, 2024). AI's advanced capabilities can increase EBITDA by 2 to 5 percentage points for B2B and B2C companies by optimizing strategic pricing functions (Hazan et al., 2021). Research, such as Assad et al. (2020), indicates that algorithmic pricing strategies can significantly boost margins, exemplified by a 38% increase in German gasoline retail margins.

AI-based price optimization offers a more nuanced approach compared to traditional rule-based models, which are limited by data constraints and a high level of aggregation. AI enables real-time insights into customer preferences, enhancing strategic investment decisions and improving sales volume, profit margins, and customer value perception. The shift from uniform to dynamic pricing models allows retailers to adjust prices in real-time based on market conditions and competitor actions. AI-driven dynamic forecasting refines price elasticity estimates using customer behavior data and external factors, improving pricing precision and profitability.

Implementing AI in pricing requires a cohesive strategy that integrates teams, processes, and technology. Leading retailers often establish centralized pricing teams or centers of excellence, integrating various functions to manage AI-driven pricing models and ensure alignment with promotions and vendor deals. AI reshapes decision-making by converting periodic price resets into continuous strategic evaluations based on market dynamics. An AI-powered pricing engine relies on an integrated data platform for real-time updates, with user-friendly tools and custom interfaces enhancing transparency, efficiency, and control over pricing decisions.

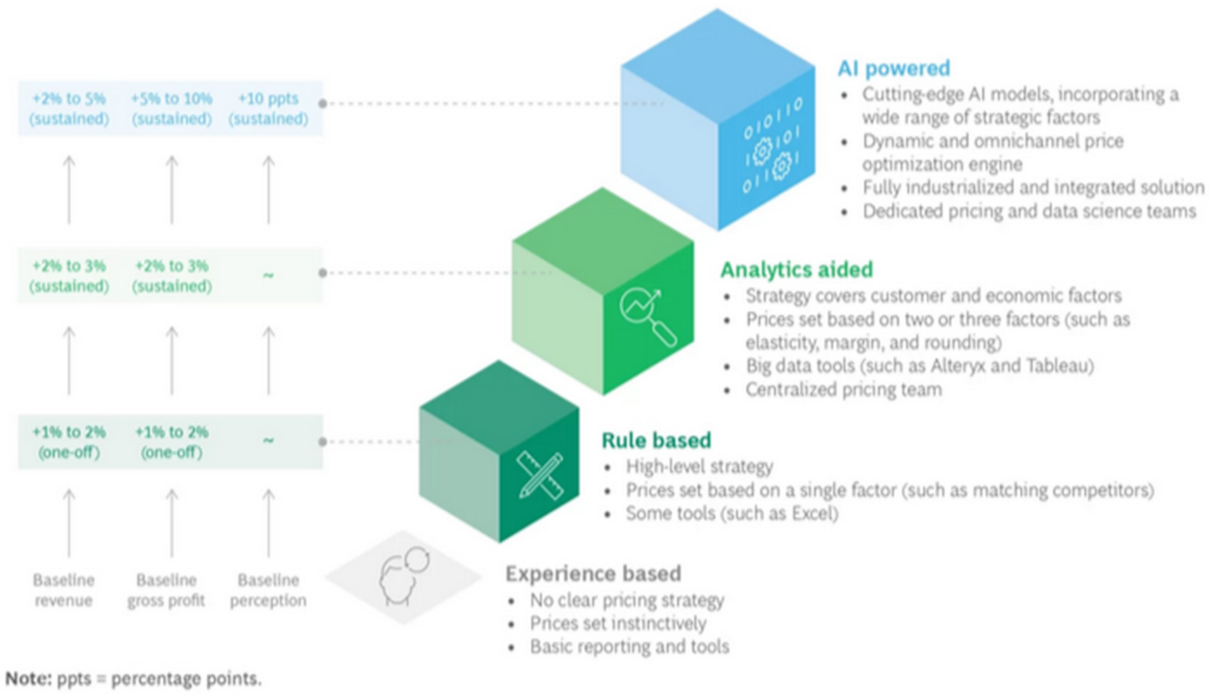

Figure 1. The impact of improving pricing capabilities
Source: Boston Consulting Group (2024)

A global AI-driven pricing survey of 1,500 companies across Europe, Asia, and the US highlights the recognition of AI-powered pricing strategies' transformative potential. However, 53% of these companies are concerned that their internal data is not sufficiently mature in quality and quantity to fully utilize AI for pricing. Although several barriers hinder broader adoption, companies that overcome these challenges find significant and tangible benefits, with AI-based pricing offering superior and measurable outcomes. The Global AI-based Pricing Study shows that 76% of respondents consider AI-based pricing essential for managing prices and enhancing profitability, yet 54% have not yet implemented it. Among users, 27% use AI for promotional optimization, 19% utilize Chat GPT, and 8% apply dynamic pricing tools, while 67% of organizations believe their IT infrastructure is insufficiently developed for AI, and 46% rely on historical transactional data for pricing (Boston Consulting Group, 2024).

Companies that successfully implement AI-based pricing follow three essential principles, as demonstrated by the superior profitability of top performers in relevant studies. first, pilot before scaling: leading firms begin by creating specific use cases, testing them through agile pilot projects, typically short-term endeavors of around four weeks. This approach allows businesses to validate smaller initiatives, such as product lines or market segments, without the risks of deploying a large-scale solution prematurely. Second, inclusive change management is crucial, with a focus on engaging the entire organization, especially sales teams, to ensure broader acceptance and mitigate resistance to new pricing models. Lastly, guidance and capacity building are key, as successful companies provide support to ensure proper use of AI-based pricing, dedicating significant time (up to 30% of the project) to data preparation, which helps set realistic expectations and enhances project outcomes (Hazan et al., 2021; Zatta, 2024).

5. CHALLENGES OF AI-POWERED PRICING

Several obstacles hinder the delegation of pricing decisions to AI, including challenges related to risk management frameworks and governance structures, which are necessary to address AI's limited accountability (Feuerriegel et al., 2022). Regulatory compliance is a significant barrier, particularly for small and medium-sized enterprises (SMEs) (Sanchez-Hughet et al., 2022). Moreover, the limited availability of skilled personnel within SMEs (Sanchez-Hughet et al., 2022) necessitates a focused approach to AI adoption in pricing. This prioritization should aim to engage the right professionals—those with expertise in specific pricing functions crucial to AI implementation, even if they lack extensive knowledge across all pricing areas (Erdmann et al., 2024).

The journey to pricing optimization through AI is fraught with numerous challenges that demand meticulous attention. *Data quality* is a fundamental concern, as the accuracy of pricing analytics is contingent upon the integrity of the data; incomplete, inconsistent, or outdated data can severely compromise results. *Model complexity* presents another significant hurdle, as AI/ML models often require substantial computational resources and expertise, which can be a barrier for smaller organizations. *Interpretability* of these models further complicates matters, making it difficult for businesses to explain and justify pricing decisions to stakeholders. Finally, the *implementation and integration of AI/ML* models into existing systems, coupled with the high *cost* of data management and specialized personnel, pose considerable challenges, particularly for companies with limited budgets.

6. ETHICAL AND LEGAL ASPECTS

The growing emphasis on generative AI by major tech companies underscores its economic and strategic importance but also highlights emerging ethical challenges. Effective integration of AI into pricing strategies requires addressing ethical and legal considerations as outlined by the European Commission (2020) and supported by research on managerial awareness of hybrid human-AI decision-making (Feuerriegel et al., 2022). The potential for unethical behavior in human resource management and the need for clear guidelines have been identified (Méndez-Suárez et al., 2023), while gaps remain in addressing ethical issues in marketing functions and developing decision support frameworks (Agarwal et al., 2024; Dwivedi et al., 2023). AI's capacity to handle vast personal data necessitates rigorous data privacy measures and algorithmic fairness to prevent discrimination (Erdmann et al., 2024; European Commission, 2020, 2024). Additionally, transparency and explainability are crucial for maintaining trust and compliance with regulatory and ethical standards (Saura et al., 2022). For AI-driven pricing, ethical considerations must be thoroughly integrated, advocating for collaborative intelligence over mere automation to ensure adherence to ethical standards (Dwivedi et al., 2023; Forth, 2024). Data privacy, informed consent, and robust security measures are vital to prevent consumer privacy infringements and regulatory issues (Namburu et al., 2022). Transparency and accountability are essential for maintaining consumer trust and preventing reputational damage (Gerlick & Liozu, 2020).

7. FUTURE RESEARCH DIRECTIONS

A key area for future exploration is the integration of AI with advanced analytics techniques, such as machine learning and natural language processing, to enhance pricing accuracy and adaptability. AI-driven optimization has been explored in contexts such as industrial processes (Al-Dhaimesh & Taib, 2023), blockchain networks (Hombalimath et al., 2023), and financial risk management (Agarwal et al., 2024), all of which underscore the necessity of further investigating automation and digitization within an increasingly complex and competitive landscape. These complexities can be broken down into multiple real-world challenges for further study. Another important direction involves addressing ethical challenges in dynamic and personalized pricing, ensuring transparency, fairness, and regulatory compliance. Research could also focus on AI solutions tailored for small and medium-sized enterprises (SMEs) to help overcome adoption barriers related to data quality and model complexity. As businesses increasingly adopt AI-driven pricing models, real-time, personalized pricing adjustments and concerns over data privacy and algorithmic bias will shape the future of pricing strategies. Additionally, as AI becomes more prevalent in pricing decisions, ethical considerations like transparency, fairness, and regulatory compliance will shape the future of AI-driven pricing, particularly with the rise of concerns over data privacy and algorithmic bias.

8. CONCLUSION

AI is revolutionizing pricing strategies across industries by enabling more accurate, dynamic, and personalized pricing models. Its ability to leverage machine learning, natural language processing, and other advanced technologies enhances demand forecasting, optimizes price setting, and boosts efficiency. However, the adoption of AI also brings challenges, such as ethical concerns around transparency, data privacy, and algorithmic bias, which must be carefully addressed to ensure fair practices. As businesses increasingly integrate AI-driven pricing, those that embrace these innovations effectively will gain a competitive edge in a rapidly evolving market landscape.

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