Chapter 10

Artificial Intelligence and The Unfairness of Pricing Strategies

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Abstract

The rapid advancement of artificial intelligence (AI) and digital technologies has transformed pricing strategies, enabling firms to implement algorithmic and dynamic pricing models. While these strategies enhance efficiency and profitability by leveraging big data and predictive analytics, they also raise significant ethical concerns. This study explores the fairness of AI-driven pricing, particularly in the context of personalized pricing strategies that adjust prices based on consumer data. Drawing from theoretical frameworks such as price fairness, distributive justice, and trust theory, the study examines consumer reactions to algorithmic pricing and the implications for long-term business-consumer relationships.

Empirical evidence suggests that personalized pricing can lead to perceptions of unfairness, especially when consumers are unaware of price differentiation or feel manipulated. While businesses argue that data-driven pricing enhances market efficiency, critics highlight risks such as privacy violations, algorithmic biases, and economic discrimination. Furthermore, AI-driven pricing strategies may exacerbate social inequalities, particularly when used in essential services such as transportation and healthcare.

This study underscores the need for balancing profit-driven pricing models with ethical considerations to maintain customer trust and social responsibility. As AI continues to shape market dynamics, a responsible approach to algorithmic pricing will be essential in fostering ethical business practices and ensuring long-term sustainability.

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1. Introduction

The development of digital technologies has changed many dynamics in the business world, and marketing has been part of this change. First and foremost, digital information technologies have made it much easier to access consumer data and use it to make decisions much more quickly. It is understood that marketing will have to be based on data, using predictive and contextual models, using the capabilities of artificial (or augmented) intelligence, augmented reality, becoming augmented marketing(Reis, 2022, p.8).

In Global audit, consulting and research firm Deloitte's Digital Marketing 2025 report (2024, p.4) we see that for CMOs, the top three priorities in the face of existing potential economic challenges are, firstly, accelerating the transition to new technologies such as AI, secondly, growth, expansion into new markets, segments and geographies, and thirdly, implementing systems and/or algorithms to improve customer personalisation.

It is noteworthy that two of the top three priorities of senior marketing executives are digitalisation and improving customer personalisation. The use of digital technologies has facilitated the tracking of customers' consumption habits and purchasing behaviour, enabling the provision of special offers, particularly with the use of personalised prices to enhance their appeal. Information technologies enable businesses to collect vast quantities of customer data at negligible cost and on a full-time basis (DalleMule & Davenport, 2017, p.112). This data can then be analysed to create sophisticated pricing strategies and personalised price recommendations based on these strategies (Priester et al., 2020, p.99).

In contemporary business organisations, there is a growing prevalence of units dedicated to the management of data, in addition to the establishment of marketing departments. These departments facilitate the creation of bespoke and personalised offers for customers, with these offers being informed by the data collected about the customers in question. The utilisation of sophisticated software and applications facilitates the aggregation of internet search behaviour, GPS location, and the diverse digital footprints emanating from individuals' digital devices. Through the analysis of this data, organisations are able to personalise advertisements, products, and services, particularly in regard to pricing, aligning with the specific needs and preferences of customers (Dubus, 2024, p.1).

The present study will focus on the extent to which the use of artificial intelligence in dynamic pricing systems is fair and ethical in terms of personalised price offers to consumers. Recent research on this subject will be referenced. The first section will emphasise the concept of price fairness. The second section will discuss research results on dynamic pricing and the use of artificial intelligence. The third section will discuss pricing strategies created by using data collected through artificial intelligence from an ethical perspective.

2. Price Fairness Concept

In early 2000, consumers noticed that Amazon was listing a DVD at different prices for different users. They then complained extensively on the company's chat boards and pressured the company to stop using the strategy of offering customers different prices for the same product (Lyn Cox, 2001, p. 264). A more recent case of differential pricing occurred on a travel platform. On the same day, a customer requested a quote from the same hotel for accommodation with three different brands of phones and the company offered different offers for each phone. Interestingly, the Iphone brand phone was offered higher than the others. Similarly, a passenger wanted to book a seat in the same class on the same flight for himself and his mother in 2022. However, the system offered his mother a cheaper price than him. In the face of different pricing for the same product, the customer expressed dissatisfaction with the unequal treatment as well as the unequal pricing (Ying et al. 2024, p.1).

Price fairness perceptions are influenced by multiple theoretical frameworks.The **Dual Entitlement Principle** (Kahneman, Knetsch, & Thaler, 1986) suggests that consumers expect fairness in transactions, accepting price increases due to rising costs but rejecting those solely for profit maximization. **Equity Theory** (Adams, 1965) and **Distributive Justice** (Homans, 1961) emphasize fairness based on input-output comparisons, where paying more than others for the same product is perceived as unjust. **Procedural Justice** (Thibaut & Walker, 1975) highlights the role of transparent and logical pricing mechanisms in shaping fairness perceptions. Similarly, **Social Comparison Theory** (Major & Testa, 1989) suggests that consumers judge fairness by comparing their price with others'. **Attribution Theory** (Weiner, 1985) explains that perceived fairness depends on whether price changes are attributed to controllable or external factors. **Trust Theory** (Mayer, Davis, & Schoorman, 1995) posits that consumer trust moderates reactions to pricing, with loyal customers being more tolerant unless they feel betrayed. Finally, **Perceived Fairness & Emotions** (Campbell, 2004) highlights the emotional dimension of fairness, where perceived price unfairness can trigger negative reactions such as anger, complaints, or negative word-of-mouth (Xia et al. 2004, p.1)

In the contemporary context, customers encountering varied prices for similar products on travel platforms may discern that these fluctuations are precipitated by numerous factors. Nevertheless, the rationales underlying price changes are frequently opaque, particularly in the context of transparent pricing practices being uncommon in the travel industry (Chung & Petrick, 2013). This engenders the perception of price fairness becoming a pivotal issue for both consumer experience and business interests. Personalised pricing has been shown to erode consumer loyalty and diminish purchase intentions by eliciting feelings of unfairness (Richards et al., 2016). In the long term, such practices can adversely impact corporate interests. Furthermore, while some tourists may exhibit self-protective or vindictive behaviour in response to price injustice, others may choose to remain indifferent. For instance, the study on the perception of price fairness on online travel platforms, published in 2024, concluded that the pricing practices of travel platforms are not yet aligned with customers' expectations of market fairness, suggesting that platforms should act in accordance with industry norms and ethical standards to maintain consumer trust (Ying et al., 2024, p. 9).

Trough the theoretical foundation for understanding how consumers perceive price fairness it is obvious that fairness judgments are not solely based on price levels but also on the rationale behind price changes, transparency, social comparisons, and emotional responses. Consumers accept price increases when they are justified by external factors, such as rising costs, but view them as unfair when they appear to be driven purely by profit motives. Social and comparative dimensions also play a crucial role, as individuals evaluate fairness relative to what others pay. Additionally, procedural aspects, such as transparency in pricing, influence fairness perceptions. Trust in the seller moderates consumer reactions, with loyal customers showing more tolerance unless they feel deceived. (Khandeparkaret. al 2020). Ultimately, fairness perceptions are not only cognitive but also emotional, meaning that unfair pricing can lead to strong negative responses, such as complaints and negative word-of-mouth (van Boom, et.al 2020).. This interpretation highlights the complexity of price fairness judgments and their implications for consumer behavior.

In the contemporary context, digital information technologies that process data collected through machine learning-based algorithms are supported by artificial intelligence to guide pricing strategies. These digital technologies are both faster and more accurate than the work to be done with human intelligence and are competent enough to manage the perception of customers. However, on the other hand, they also affect the perception of price fairness.In this context, it is important to know which factors affect the perception of price fairness. The following components, as outlined by the framework developed by Xia et al. (2004, pp. 1-2), have been identified as influential factors in determining consumers' perceptions of price fairness:

i) transaction similarity and the selection of the comparison party;

ii) the allocation of costs and profits with the concomitant attribution of responsibility;

iii) the status of the buyer-seller relationship (trust); and

iv) knowledge, beliefs, and social norms.

The interplay of these factors collectively influences consumers' cognitive and emotional perceptions of price fairness. In addition, depending on the perceived value and emotions, they also affect the decision-making process of consumers. Some consumers may not take any action, while others may consider taking revenge. Some customers even report deficiencies related to price unfairness and socially unfair behaviour (Martin et al. 2009).

3. Dynamic Pricing and Artificial Intelligence

The concept of dynamic pricing, which gained prominence in the 1980s following its successful implementation by American airlines, also resulted in the adoption of algorithmic pricing. While the mathematical concepts and models underpinning dynamic pricing can be traced back to the mid-twentieth century, it was the seminal scientific papers of Peter Belobaba (1987, 1989) in the late 1980s and early 1990s that generated increased interest in practical studies (Seele et al. 2019, 700).

Personalised pricing is predicated on the utilisation of algorithmic pricing, a practice that airline companies have employed in revenue management software for a considerable duration. In its nascent form, the software's pricing mechanisms were governed by instructions provided by a programmer.Contemporary algorithms, however, are driven by artificial intelligence and exhibit a marked increase in autonomy when compared with their antecedents. These advanced algorithms have evolved to formulate pricing strategies through active experimentation and in accordance with the evolving or changing environment. They demonstrate a high degree of autonomy and require minimal or no instruction from an external programmer. However, the employment of algorithms in pricing strategies gives rise to legal and ethical concerns. These algorithms may be designed to orchestrate price increases or diminished competition, obviating the need for direct communication or agreement (Calvano et al., 2020, pp.3-4). This may present challenges in terms of competition law and consumer rights, potentially necessitating the establishment of regulatory frameworks to promote the development of more transparent and auditable algorithms.

There are different types of algorithmic pricing. The best known of these is dynamic pricing. Dynamic pricing, sometimes referred to as surge, yield, or real-time pricing, refers to the practice of dynamically adjusting prices to realise revenue gains when responding to a specific market situation with uncertain demand. Personalised pricing can also be seen as first-order price discrimination, customised or targeted pricing and represents a pricing strategy in which 'firms charge different prices to different consumers according to their willingness to pay' (Seele et al. 2019, pp. 699).

Demand forecasting, flexibility and the willingness to pay are pivotal to a profitable pricing strategy. For instance, a study conducted in the context of grocery retailers (Srinivasan et al., 2008) found that demand assessments, rather than changing prices from week to week based on wholesale costs and competition, lead to higher profits. Dynamic pricing also micro-segments the market by person, product, period and location in order to adjust the price. Prices are adjusted as these four basic dimensions change. (Kopalle et al. 2023, p.581)

Industries such as supermarkets, airlines and credit card companies collect traces left by individual consumer transactions in large databases to examine purchasing patterns and offer personalised price offers through targeted marketing strategies. On the one hand, there are those who argue that consumers served at higher prices have the potential to affect competition and that this situation will lead companies to abandon dynamic pricing. However, an analysis of actual market behaviour reveals that price adjustments based on customer segments do not necessarily result in reduced profits for companies, even when consumers are aware of these strategies (Laussel & Resende, 2022).

Algorithmic pricing has emerged as a crucial aspect of dynamic pricing in response to changes in customer segments. Wang, Li, and Kopalle (2022) define algorithmic pricing as the use of artificial intelligence algorithms by businesses to identify, analyze, and offer personalized prices to consumers. Today, companies equipped with advanced big data analytics can effortlessly track consumers' digital footprints to determine their preferences. In the retail sector, Target analyzes customers' past shopping behaviors to provide personalized discount coupons. Similarly, in the travel and hospitality sector, Orbitz engages in price discrimination by tracking online browsing activities The use of consumer data is not limited to online retailers but extends to physical stores as well. For instance, Amazon's cashierless "Amazon Go" stores utilize cameras and sensors to identify customers, monitor their in-store movements and product interactions, and offer personalized discounts (Vandervoort, (2024). In China, particularly among luxury brands, stores employ facial recognition technology at entrances to identify individuals and implement personalized pricing strategies (Wong, 2018).

4. Ethical Aspect of Pricing Strategies

The use of algorithmic pricing and data-driven personalisation in competitive markets has ethical implications for customer privacy. While competition requires independent decision-making, Gal (2019) highlights how algorithms now enable autonomous price coordination, potentially leading to implicit collusion among competitors. This raises legal concerns, particularly when algorithms are designed to react to competitors' pricing decisions in a way that maintains coordinated market outcomes.

Simultaneously, businesses leverage vast data resources to enhance personalized marketing strategies, shifting from broad customer segmentation to individualized targeting. However, Turow (2017, pp. 247–248) in his book "*The aisles have eyes: How retailers track your shopping, strip your privacy, and define your power*" warns of ethical dilemmas in this practice, as algorithms may facilitate social discrimination by tailoring messages and prices based on consumer profiles 'often without the individuals' awareness or consent. These developments underscore the tension between technological advancements, market fairness, and ethical considerations in modern digital economies.

It is also addresses the legal accountability of algorithm designers and users in cases of potential anti-competitive behavior. The European Commissioner for Competition emphasizes that businesses remain responsible for the consequences of the algorithms they implement. Legal liability arises when a company is aware of the algorithm's pricing effects, as demonstrated in the *Eturas* case, where 30 Lithuanian travel agencies used a shared booking system that restricted discounts. The European Court of Justice ruled that awareness of the algorithmic restriction was necessary to establish a cartel agreement, though indirect awareness—such as ignoring the algorithm's potential effects—could also be relevant. However, the legal framework remains unclear regarding situations where algorithms autonomously determine pricing strategies and facilitate collusion without explicit human intervention. This ambiguity raises ongoing legal and ethical challenges in regulating algorithmic decision-making in competitive markets (Gal, 2019, p.20).

Personalised pricing is a tool utilised across various sectors, with its efficacy in enhancing business profitability being particularly pronounced in contexts characterised by minimal marginal costs of production (Coker & Izaret, 2021, p.387). To illustrate this point, consider the observation made by Shiller (2016, p.7), who asserts that Netflix could potentially augment its profits by up to 15% through the strategic tailoring of its pricing structure to customers' web browsing histories.

Steinberg (2020) critiques big-data-driven personalized pricing, arguing that its exclusive use for profit maximization disrupts the fair distribution of economic benefits. He asserts that such pricing strategies deepen power asymmetries between consumers and firms, undermining relational equality in market transactions. By making it prohibitively difficult for consumers to compare prices or negotiate, personalized pricing diminishes their agency as market participants, effectively limiting their ability to make informed purchasing decisions. This perspective highlights the ethical concerns surrounding the practice, suggesting that personalized pricing may be morally indefensible if it violates principles of fairness, equal treatment, and market accessibility.

It is the right of consumers to demand transparency regarding the benefits they accrue from specific market practices, particularly in terms of price. Previous research suggests that consumers' acceptance of a price depends on their perception of its fairness, which is judged by whether a transaction is reasonable, acceptable, or just. Unfair pricing practices trigger negative consumer reactions, including distrust, reduced purchase intentions, and increased likelihood of switching to competitors. Moreover, perceived price unfairness leads to negative word-of-mouth, both privately and publicly, further harming a company's reputation and customer loyalty (Hufnagel et al. 2022, p.347). For consumers, lack of transparency in pricing leads to the perception of arbitrary pricing, which may lead to scepticism and questioning of the firm's credibility.

The increasing role of digitalisation and algorithmic decision-making in dynamic pricing highlights the technological advances that are transforming pricing strategies. The rise of online retail, digital travel booking, and mobile commerce, accelerated by the COVID-19 pandemic, has enabled real-time, personalized pricing. Innovations such as electronic shelf labels in physical stores allow retailers to adjust prices dynamically, bridging the gap between online and offline pricing. Additionally, the shift from human-driven to algorithmic-driven pricing decisions has led to autonomous pricing agents setting prices without direct managerial intervention. This automation reduces the cost of price adjustments, making dynamic pricing more accessible and widely adopted (Kopalle et al., 2023, p.589)

On the other hand it must be noted that dynamic pricing enabling price collusion, which can lead to monopolistic or oligopolistic practices. Legal cases, such as the 2015 "Poster Cartel" case on Amazon, have demonstrated how pricing algorithms can be used to maintain price parity among vendors, effectively preventing price competition. While some cases involve explicit collusion where vendors coordinate pricing strategies more concerning is tacit collusion, where autonomous pricing algorithms unintentionally synchronize prices without direct human intervention. This occurs due to advanced machine learning techniques, such as reinforcement learning, which allow algorithms to adjust prices in response to competitors' pricing patterns. Two key challenges arise from this: first, existing legal frameworks focus on human collusion, making algorithm-driven collusion difficult to regulate; second, the complexity and speed of algorithmic pricing make it difficult to detect and analyze collusion, requiring extensive computational resources. These factors present significant ethical and regulatory challenges in the use of dynamic pricing. (Nunan & Di Domenico, 2022, pp.454-455).

There are studies that argue against the ethics of price customization. Marcoux (2006) and Elegido (2014) have conducted studies that argue that it is more ethical to offer the same product to different consumers at different prices, namely through price customization, with a unitary price set under open market conditions. A comprehensive review by Coker and Izaret (2021) opposes these studies and argues that price customization is more ethical than unitary pricing. Through a structured example involving these two consumer types, they evaluate price personalization using four Social Welfare Functions (SWFs)—utilitarian, egalitarian, prioritarian, and leximin. Their findings indicate that price personalization enhances overall social welfare across all four SWF perspectives. Ultimately, they conclude that personalized pricing not only increases total welfare but also benefits consumers, challenging traditional ethical concerns associated with differential pricing strategies (Mazrekaj et al.2024)

Besides these studies Mazrekai et al (2024) evaluates the ethical implications of unitary versus personalized pricing through the lens of four consequentialist Social Welfare Functions (SWFs). Their findings challenges the conclusions of Coker and Izaret (2021), who argued that personalized pricing is ethically superior due to its ability to increase both utility and equity. The authors caution that this conclusion is contingent on the assumption that wealthier individuals derive higher utility from a product. When this assumption is relaxed, the ethical advantage of personalized pricing diminishes, particularly if consumers perceive it as unfair or feel their privacy is violated by AI-driven willingness-to-pay (WTP) estimations. The study suggests that unitary pricing may often be preferable if personalized pricing results in a welfare loss, especially when product utility is significant for lower-income consumers. More broadly, the findings highlight the need for a nuanced approach to ethical evaluations, as different economic and behavioral conditions can lead to unexpected reversals in outcomes.

Algorithmic price personalization has an impact on consumer perceptions of fairness. Zuiderveen Borgesius & Poort (2017, p.354) argue that consumers feel wronged when charged higher prices than others, perceiving such practices as unfair or manipulative, which can lead to reduced demand. Hermann (2022, p.52) further emphasizes the ethical dilemmas associated with algorithm-driven pricing, particularly its potential to reinforce social inequalities. When algorithms segment populations based on demographic factors, they may unintentionally favor or disadvantage certain customer groups. Biases in algorithmic predictions can stem from skewed data, including disproportionate representation of certain groups, misleading proxy variables, or insufficient data, leading to unfair and discriminatory outcomes. Mazrekaj et al. (2024) reinforce this concern by stressing that these biases can result in unequal treatment of individuals, raising significant ethical and fairness-related challenges in algorithmic pricing strategies.

Empirical research consistently demonstrates that consumers perceive personalised pricing as unfair or manipulative (Anderson & Simester, 2010; Krämer et al., 2018; Turow et al., 2005). A survey that was held by Turow and his friends (2005) in USA about online an doffline shopping and price discrimination. The study reached to 1,500 U.S. adults and revealed that 76% of respondents expressed concern regarding others paying less for the same product. On the other hand 64% of American adults who have used the internet for shopping do not know it is legal for “an online store to charge different people different prices at the same time of day.” 71% don’t know it is legal for an offline store to do that. And also 75% do not know that besides a website has a privacy policy, it may share the information of the visiters with other websites and companies. (Turow et al., 2005, p.3). Price discrimination is frequently perceived negatively, even when it benefits the consumer, as evidenced by the fact that 72% of respondents disagreed with the notion that stores should offer them lower prices to retain their loyalty. The perception of unfair pricing has been demonstrated to have significant consequences, with Anderson and Simester (2010, p.729) finding in a randomised field experiment involving over 50,000 customers that consumers who discovered price disparities were less likely to make future purchases from the retailer. These findings highlight the potential negative impact of personalised pricing on consumer trust and long-term business relationships.

According to the study of Krämer et al., (2018) about airline pricing driven by low-cost carriers, consumer knowledge about personal pricing is crucial in determining whether they perceive a deal as fair. Resistance to personal pricing is expected due to concerns over privacy, data sharing, and perceived price manipulation. In the short term, airlines that refrain from using personalized dynamic pricing may gain a competitive edge if customers feel exploited. However, if all major carriers adopt personalized dynamic pricing, customers may have no alternative but to accept it—much like how revenue management and advance purchase restrictions became industry norms despite initial resistance.

Nevertheless, gaining customer acceptance for personalized dynamic pricing will be more challenging than implementing traditional revenue management practices. From the airlines aspect to be successful, airlines must effectively communicate and justify personalized pricing as fair, especially as privacy and discrimination concerns become widespread. At that point two key risks require further analysis: first, whether personalized pricing provides meaningful value to customers despite its economic advantages, and second, whether the short-term revenue gains from real-time willingness-to-pay estimation outweigh the long-term risks of damaging customer relationships. Ultimately, consumer perceptions of fairness (Alderighi et al., 2022) will be crucial in determining the viability and success of personalized dinamic prising in the airline industry.

An important disccusion point is the ethical concerns surrounding digital surveillance and privacy in the context of personalized pricing. Unlike the "access-view" of privacy, where individuals simply relinquish their data, people selectively share information with third parties while maintaining expectations about its scope, access, and usage. Ethical concerns arise when consumers feel coerced into sharing their data, such as when insurance companies charge higher premiums to those unwilling to disclose personal information. Loi et al. (2022, p.8) argue that this a practice that constitutes psychological coercion. This form of digital surveillance not only undermines privacy preferences but also limits individual autonomy, authenticity, and spontaneity in decision-making. Since personalized pricing relies on algorithms that estimate a consumer's willingness-to-pay using collected data, it may create a sense of being monitored, leading to a perceived loss of utility (Priester et al., 2020; Turow et al., 2015; Zuiderveen Borgesius & Poort, 2017). Some individuals may reject data-sharing entirely, not because of specific consequences, but because they intrinsically value privacy (Loi et al., 2022). These concerns highlight the ethical and psychological implications of data-driven pricing strategies.

5. Conclusion

As artificial intelligence and data-driven strategies continue to reshape pricing mechanisms, the ethical and practical implications of algorithmic pricing become increasingly significant. While dynamic pricing offers firms a powerful tool to optimize revenue and balance supply and demand, its implementation must be approached with caution. The intersection of AI and pricing strategies presents both opportunities and challenges—ranging from increased efficiency to concerns over fairness, transparency, and consumer trust.

Striking a balance between profitability and ethical responsibility is crucial for businesses aiming to maintain long-term customer relationships. As discussed, algorithmic pricing can inadvertently lead to consumer dissatisfaction, particularly when price adjustments appear exploitative or opaque. In industries where pricing directly affects essential services, such as transportation and healthcare, the need for responsible governance becomes even more pronounced. Regulatory oversight, corporate self-regulation, and interdisciplinary collaboration between scholars and practitioners will play a pivotal role in shaping the future of fair and effective pricing strategies.

Moving forward, businesses must not only refine their AI-driven pricing models to enhance accuracy and adaptability but also integrate ethical considerations into their decision-making processes. Transparent communication, consumer education, and proactive policy-making will be essential in ensuring that AI-powered pricing benefits both businesses and society at large. By fostering a responsible approach to pricing strategy, firms can harness the advantages of AI while mitigating risks, ultimately creating a more sustainable and consumer-centric marketplace.

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