

The Paradox of Algorithmic Pricing: How “Big Data Price Discrimination” Affects Consumer Trust and Repurchase Intention

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Abstract

With the rapid development of e-commerce and the sharing economy platforms, algorithmic pricing has evolved from a macro-level market supply and demand adjustment tool into a micro-level “perfect price discrimination” based on individual consumer behavior data, also known as “big data price discrimination.” This paper systematically reviews the profound impact of big data price discrimination on consumer psychology and behavior. This study points out that most companies face a core “pricing paradox”: while algorithmic pricing can maximize a company's economic surplus in a single transaction, this behavior, which violates traditional pricing norms, triggers strong consumer perceptions of unfairness. Literature indicates that consumers' negative attributions to data misuse directly destroy their cognitive and emotional trust in the platform, leading to a precipitous decline in platform satisfaction and repurchase intention. This paper reveals the specific mechanisms of this trust loss by comparing unpredictable price fluctuations with behavior-based user profiles, and provides management insights for companies on how to design fair pricing in the algorithmic era.

Keywords

algorithmic pricing, big data price discrimination, perceived fairness, consumer trust, repurchase intention

1. Introduction

In the contemporary digital economy, the diffusion of big data analytics and machine learning has allowed online platforms and e-commerce retailers to adopt real-time, highly granular dynamic pricing architectures. Uniform pricing, once the standard, has to a large extent yielded to algorithmic pricing. As a dynamic pricing model grounded in a dense matrix of variables, algorithmic pricing relies on artificial intelligence systems to recalibrate the prices of goods on an ongoing basis. Among the variables typically incorporated are real-time supply conditions, market demand, competitor conduct, and, above all, individual consumer profiles. Under these conditions, dynamic pricing turns into the highly contested practice commonly termed “big data price discrimination” when algorithms modify prices according to consumers’ purchase histories, search frequency, and predict price elasticity [1].

Set against these technological shifts, contemporary firms have been pushed into a genuine strategic dilemma. From a microeconomic standpoint, personalized pricing derived from large-scale data is distinctly appealing to online businesses because it approximates perfect first-degree price differentiation. In practical terms, this approach enables digital market platforms to extract buyers' surplus more fully while increasing short-term economic returns [1]. From the standpoint of consumer psychology, however, a sharp countervailing pattern appears: consumers frequently respond with resistance once they realize that their personal information is being used to generate additional profit. Here, then, the central contradiction emerges—the dilemma of automated pricing. To enhance performance and maximize transaction value may, in the longer run, undermine corporate durability, with long-term stability depending heavily on customer loyalty and brand reputation [2].

At the intersection of automated pricing and consumer psychology, the stakes are not merely academic. For scholarship, the issue bears directly on how fairness perceptions, trust judgments, and purchase intentions are formed under data-intensive market conditions; for managers, the implications are immediately operational. With international organizations now examining the procedural fairness of major technology firms ever more closely, insight into consumer responses to personalized pricing has moved well beyond the status of a tactical promotional concern and become a core matter of organizational governance, consumer welfare, and ethical leadership.

Against that backdrop, the present study addresses three closely linked academic questions. First, which conceptual pathways account for the manner in which data-driven personalized pricing shapes consumers' perceptions of price fairness? Second, through what mechanisms do price fluctuations and episodes of abnormal charging weaken trust in its different forms? Third—and this is the downstream issue—how does this erosion of trust affect consumers' willingness to make future purchases?

2. Theoretical Background

To understand consumer resistance to machine-driven pricing and big data price discrimination (BDPD), psychological insight has to be read alongside behavioral economics. At the level of underlying mechanism, consumer responses to personalized pricing rest on three interlocking concepts: dual entitlement theory, the buyer motivation allocation framework, and perceived cost inequality [2, 3].

At the starting point of this model lies price inequality. The purchasing right, in this account, is not evaluated in isolation but relationally. Consumers benchmark present costs against prices earlier or against the amounts paid by peers. In conventional retail environments, standardized pricing structures tend to preserve a degree of psychological equilibrium; under automated pricing systems, by contrast, that equilibrium is disrupted, sometimes quite abruptly. Upon learning that peers obtained identical goods at lower prices because algorithmic profiling sorted buyers differently, consumers commonly register a pronounced sense of having been cheated. From that perception of unfairness follow negative responses—disappointment, anger, and, in some cases, a more diffuse sense of exploitation. Rapid deterioration in trust between firms and customers then becomes likely [2].

Seen through the lens of the dual rights principle, the line separating acceptable price flexibility from unfair machine-driven discrimination becomes easier to specify. The principle holds that firms are entitled to a basic level of profit, whereas consumers are entitled to a fair basic expenditure [2, 4]. In general, price increases tied to broad economic strain or rising operating costs are tolerated by consumers [5]. Very different, however, pricing systems are solely to extract the maximum possible payment from individual customers, absent any corresponding increase in business costs—in ordinary terms, such systems are read as straightforwardly greedy. BDPD violates this principle for precisely that reason: its price variation arises from concealed information collection rather than from legitimate cost-side pressures.

Finally, the framework explaining how buyers allocate their motivations helps account for the intensity of retaliatory behavior. Once unusual pricing differences are noticed, consumers tend—almost immediately—to ask why those differences [3]. If elevated charges are attributed to external economic conditions outside the supplier's control, market confidence remains comparatively intact. Where the same disparities are instead attributed to deliberate, opaque manipulation by suppliers, both rational belief and emotional trust are sharply weakened [3].

Taken together, these three concepts indicate that BDPD constitutes a markedly complex social dynamic, one capable of generating substantial psychological distress among consumers, rather than functioning merely as a financial value-enhancing instrument.

3. Literature Review

3.1 The Economic Rationality and Basis of Consumer Identification

To fully analyze consumer resistance to algorithmic pricing, it is essential to first understand the economic motivations behind companies implementing this strategy. Acquisti and Varian laid the foundation for research in this field, systematically exploring the economic incentives behind “adjusting prices based on purchase history” using complex game theory models [1]. Their research demonstrates that in the digital retail market equipped with advanced “customer identification” technology, highly rational companies have a strong incentive to implement differentiated pricing. By meticulously tracking consumers' historical transaction records, browsing frequency, and device data, pricing algorithms can accurately distinguish between price-sensitive new users and price-inelastic, highly platform-dependent loyal customers.

Based on the theoretical derivation of Acquisti and Varian, companies can rapidly expand market share by offering highly attractive “entry discounts” to new users, while simultaneously leveraging the opacity of big data to charge higher prices to more loyal customers—a practice commonly known as “loyalty penalty” [1, 6]. This mathematical model successfully demonstrated that, in the digital ecosystem, first-degree (or full) price discrimination is not only technically feasible but also the absolutely optimal strategy for maximizing single-transaction firm profits and obtaining maximum consumer surplus. However, this study itself suffers from the limitations of traditional microeconomic theory: it models consumers as perfectly rational, emotionless utility-maximizing agents. This purely “economic rationality” sows the seeds for future business crises because it completely ignores consumers' sensitive needs for social fairness and emotional fluctuations when faced with implicit price differences.

3.2 Psychological Roots of Unfairness in Dynamic Pricing

As online retail platforms began to widely adopt real-time dynamic pricing algorithms, marketing scholars quickly discovered a significant gap between economic optimization models and actual negative consumer reactions. Xia proposed the groundbreaking conceptual framework of “price unfairness”, which became the theoretical cornerstone of all subsequent behavioral pricing research [2]. This framework argues that consumers' price evaluation is not an isolated mathematical calculation; rather, it is a highly sensitive social comparison process that largely depends on a “reference point”. When consumers perceive that the current algorithmic price contradicts their historical reference price or violates the “dual rights principle” (i.e., businesses have the right to a reasonable profit, and consumers have the right to a reasonable price), they experience strong cognitive dissonance and a sense of unfairness.

Based on this theory, Haws and Bearden shifted their research focus from the flow of corporate profits to the flow of consumer psychological perceptions through a series of rigorous controlled experiments [7]. Their findings pose a serious challenge to purely economic models: even if consumers have never experienced personalized discrimination, simply being aware of frequent and dynamic price fluctuations can significantly exacerbate their purchase anxiety [7, 8]. Haws and Bearden demonstrated that frequent and unexplained price changes can increase consumers' cognitive load and search costs psychologically [7]. To avoid the double frustration of “paying more than others,” consumers will actively postpone their purchase decisions and prolong the price comparison period, ultimately leading to a significant decline in overall shopping satisfaction.

3.3 Disruptive Pricing Events and Their Disruptive Consequences

Garbarino and Maxwell further explored the boundaries of dynamic pricing, proposing the key concept of “disruptive pricing events.” They argued that although the online business ecosystem relies on virtual algorithms, the underlying social contract is still constrained by implicit pricing norms, such as cost-based uniform retail pricing, which have gradually formed over hundreds of years of human commercial activity [5].

Gabarino and Maxwell's empirical research shows that when the scale or logic of algorithmic pricing completely breaks these implicit social norms—for example, an algorithm immediately raises the price of necessities based on an individual's urgent search behavior without a corresponding increase in supply chain costs—consumers' psychological reactions deteriorate dramatically [5]. Consumers no longer make rational cost-benefit calculations as described by Xia [2]; instead, they feel strongly exploited and deeply psychologically betrayed. Garbarino and Maxwell found that this emotion is highly destructive [5], prompting consumers to shift from passive anxiety to active retaliatory behavior. After experiencing a pricing violation incident, consumers are highly likely to actively participate in spreading negative word-of-mouth, file formal complaints, and ultimately leave the platform altogether, indicating that the algorithmic violation fundamentally damages the brand's long-term value.

3.4 Data-Driven Discrimination, Consumer Attribution, and the Deconstruction of Trust

The forefront of academic research has shifted its focus to an extreme manifestation at the intersection of big data and machine learning: algorithmic price discrimination based on individual behavioral characteristics. Under the conceptual framework of perceived price unfairness, such perceptions trigger strong negative emotions, ranging from mild disappointment to intense anger and a sense of exploitation [3].

Through structural equation modeling of e-commerce users, consumer trust is subdivided into cognitive trust—representing the recognition of a platform's technological capabilities—and emotional trust, which reflects trust in the platform's goodwill, ethics, and concern for consumer well-being [3]. Their research revealed an extremely dangerous corporate signal: when consumers realize that the behavioral traces they voluntarily left, such as browsing preferences and loyalty metrics, are systematically leveraged by algorithms to impose first-degree financial premiums, they exhibit extremely high attribution sensitivity. Consumers will not hesitate to attribute this discrimination to malicious manipulation and pure commercial greed by the platform [9]. Research shows that while this malicious internal attribution has a limited impact on cognitive trust, users still believe the application operates efficiently, it has a devastating impact on emotional trust [3]. The collapse of emotional trust is the main and most critical mediating factor leading to a sharp drop in repurchase intention to zero.

4. Key Finding

4.1 The Absolute Conflict Between Economic Optimization Models and Behavioral Psychology

Integrating previous studies into one cohesive conceptual model vividly exposes an essential dilemma regarding automated fee-setting. Purely financial simulations mathematically prove how tailored charging acts as a highly effective tool to capture buyer reserves while boosting enterprise revenue [1]. However, such financial reasoning severely conflicts with the way individuals naturally think, since people strongly depend upon ideals of equity and moral rightness [2].

Various observational investigations [3, 5] repeatedly reveal how individuals assess commercial exchanges based profoundly on societal notions of equitable wealth allocation. Whenever automated systems accurately pinpoint and exploit a shopper's highest spending limit, those identical systems heavily violate the buyer's mental safety zones. Corporations might face enduring fiscal catastrophes as a consequence. A localized victory secured by software during one individual exchange ultimately morphs into an absolute strategic failure regarding overall corporate identity, wiping out the entirety of a patron's customer lifetime value (CLV). This stark contradiction between cold economic rationality and human psychological resistance is precisely the most critical strategic blind spot facing digital platforms today.

4.2 Escalating Harm: The Opacity and Intrusiveness of Pricing Mechanisms

Reviewing contemporary studies uncovers distinct levels of damage regarding buyer acceptance of dynamic pricing. Ordinary cost variations, like airline tickets adjusting based on aggregate demand, might provoke shopper unease. Yet, people typically blame external market forces instead of intentional business hostility, making the resulting fallout relatively controllable [7]. Once this valuation process morphs into big data price discrimination, however, the subsequent brand backlash multiplies massively [3].

What truly separates both contexts is how secretive and invasive the underlying pricing mechanism actually is [10]. Employing big data price discrimination poses a direct threat to personal privacy. Should automated systems punish steadfast patrons, these shoppers experience intense injustice alongside deep indignity, feeling their faith was aggressively manipulated [5]. Consequently, mental distress inflicted via stealthy software evaluations vastly exceeds the injuries stemming from open, market-based dynamic pricing.

Importantly, such severe emotional wounds do not remain dormant; they consistently spark deliberate pushback and tactical opposition from buyers. Whenever charging tactics shatter unwritten community standards and make individuals feel used, purchasers transition from mere worry toward hostile revenge. This shift yields devastating public complaints and permanent service abandonment [5]. Destroying affective reliance eventually causes an immense drop in future buying desires, completely neutralizing whatever short-term economic gains the code initially secured [3]. Moreover, becoming familiar with hidden algorithmic strategies empowers patrons to deploy sophisticated defenses. Tactics include altering search records or creating diverse login identities, all aimed at intentionally tricking the vendor's digital tracking apparatus [11]. Ultimately, the stealthy extraction of consumer surplus sets off an ongoing loop of buyer retaliation. This forces commercial results away from achieving local optima during single exchanges, driving them toward an absolute destruction of customer lifetime value.

5. Discussion

5.1 Mitigation Strategies: Shifting to “Fair Design”

To address this paradox, the conceptual framework proposed by Xia et al. offers a crucial breakthrough: the perception of unfairness largely depends on the “reasonableness” of price differences [2]. Digital platforms must shift towards a “fair design” strategy, completely abandoning covert price increases targeting loyal users.

Businesses should no longer engage in opaque discrimination but should structurally redefine price differences, transforming them into transparent “rewards or discounts for specific behaviors” rather than “identity-based penalties.” If an algorithm identifies high-value customers, the system should leverage these customers to enjoy personalized value-added services or explicit promotional discounts, rather than secretly raising the base price. Only by fundamentally transforming the algorithmic architecture, shifting from a “value-extracting” model to a “value-empowering” model, can e-commerce companies escape the predicament of consumer distrust.

5.2 Research Limitation

While existing literature effectively traces the theoretical evolution from economic optimization [1] to pervasive dynamic pricing anxiety [7], and ultimately to destructive betrayal and the complete collapse of trust [3], significant research gaps remain. Most behavioral studies rely on short-term situational simulations or cross-sectional surveys, with a severe lack of longitudinal, field data. How consumers dynamically adjust their “resistance strategies” (e.g., using VPNs or one-off accounts to cheat algorithms) over years of platform use remains under-examined [11]. Furthermore, there is a lack of comparative studies on how different regulatory frameworks affect consumers’ perceived benchmarks of unfairness.

5.3 Future Research

Future research urgently needs to conduct experiments in real-world e-commerce ecosystems to empirically test whether proactive and transparent disclosure of algorithmic rules can effectively guide consumers to make positive attributions and promote trust restoration. Furthermore, researchers must place great emphasis on cross-cultural research, examining how different definitions of fairness in data privacy laws and cultures mitigate consumer resistance to algorithmic discrimination, ultimately providing a universally applicable theoretical foundation for global digital governance.

6. Conclusion

At the micro level, this review lays bare the behavioral consequences associated with algorithmic pricing and big data price discrimination. Across the existing academic literature, a repeated conclusion emerges: when

online marketplace platforms pursue perfect price discrimination with relentless consistency, the outcome is the algorithmic pricing paradox. What comes into view here is an internal contradiction—immediate transaction gains on one side, long-horizon brand value on the other. Because such automated tools routinely trespass against implicit societal norms surrounding costs (norms that consumers appear to treat as baseline expectations), they generate negative consumer evaluations under the rubric of price unfairness. In the end, emotional trust on the buyer side declines sharply, thereby extinguishing any intention to repurchase in the future.

Of the analysis's principal scholarly contributions, the most salient is its bridging of the long-standing divide between quantitative pricing-optimization models and qualitative consumer psychology. Drawing on attribution theory, the study identifies declining emotional trust as the key behavioral mediator—more precisely, the variable through which the broader pattern becomes intelligible. In that sense, this factor explains why ostensibly ideal economic algorithms fail once they are placed in real-world commercial settings.

References

- [1] Acquisti, A., & Varian, H. R. (2005). Conditioning prices on purchase history. *Marketing Science*, 24(3), 367–381. <https://doi.org/10.1287/mksc.1040.0103>
- [2] Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price unfairness perceptions. *Journal of Marketing*, 68(4), 1–15. <https://doi.org/10.1509/jmkg.68.4.1.42733>
- [3] Chen, Y., Zhu, Y., & Chen, H. (2021). Data-driven discrimination, perceived fairness, and consumer trust: The perspective of consumer attribution. *Frontiers in Psychology*, 12, Article 748765. <https://doi.org/10.3389/fpsyg.2021.748765>
- [4] Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). Fairness as a constraint on profit seeking: Entitlements in the market. *The American Economic Review*, 76(4), 728–741.
- [5] Garbarino, E., & Maxwell, S. (2010). Consumer response to norm-breaking pricing events in e-commerce. *Journal of Business Research*, 63(9), 1066–1072. <https://doi.org/10.1016/j.jbusres.2008.12.012>
- [6] Fudenberg, D., & Tirole, J. (2000). Customer poaching and brand loyalty. *The RAND Journal of Economics*, 31(4), 634–657. <https://doi.org/10.2307/2696352>
- [7] Haws, K. E., & Bearden, W. O. (2006). Dynamic pricing and consumer fairness perceptions. *Journal of Consumer Research*, 33(3), 304–310. <https://doi.org/10.1086/508441>
- [8] Grewal, D., Hardesty, D. M., & Iyer, G. R. (2004). The effects of online dynamic pricing on consumer perceptions of fairness. *Journal of the Academy of Marketing Science*, 32(3), 259–275. <https://doi.org/10.1177/0092070304265752>
- [9] Campbell, M. C. (1999). Perceptions of price unfairness: Antecedents and consequences. *Journal of Marketing Research*, 36(2), 187–199. <https://doi.org/10.1177/002224379903600205>
- [10] Bleier, A., & Eisenbeiss, M. (2015). The personalized advertisement flexibility paradox: The interplay of privacy concerns, trust, and effectiveness. *Journal of Marketing*, 79(2), 112–130. <https://doi.org/10.1509/jm.12.0460>
- [11] Friestad, M., & Wright, P. (1994). The persuasion knowledge model: How people cope with persuasion attempts. *Journal of Consumer Research*, 21(1), 1–31. <https://doi.org/10.1086/209380>

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Conflicts of Interest

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