Proceedings of ICEMGD 2025 Symposium: The 4th International Conference on Applied Economics and Policy Studies
DOI: 10.54254/2754-1169/2025.BJ24935

AI Algorithmic Pricing for Online Platforms: A Literature Review

Lixun Song[1*†], Changhao Chen[2†], Federick Lin[3†]

[1] University of New South Wales, Sydney, Australia,
[2] Shenzhen College of International Education, Shenzhen, China
[3]Charterhouse School, Godalming, England
**Corresponding Author. Email: z5528296@ad.unsw.edu.au*
[†]These authors contribute equally to this paper and should be considered as co-first authors.

Abstract. Rapid advances in Artificial Intelligence (AI) are reshaping the economic landscape, creating opportunities and challenges for businesses, consumers, and policymakers. These technologies are changing market dynamics by optimizing collusive pricing and altering the competitive landscape. Therefore, we summarized the relevant literature and explored the following questions in depth: Will algorithmic decision-making promote competition or lead to new market concentration and collusion forms? How will AI-driven automation affect dynamic pricing on online platforms? How does price discrimination compare to consumer behavior? What are the current regulatory challenges and antitrust laws? This research paper presents a well-structured review of existing literature on AI algorithmic pricing in online platforms and explores the economic implications. We first examine the evolution of pricing mechanisms, contrasting traditional models with AI-driven approaches, including dynamic and personalized pricing. Next, we consider the use of AI-driven algorithms in competition and explore how these algorithms bring about capacitation, leakage of price information, and market dominance. Then, we consider consumers' responses to algorithms through AI-based pricing, and we take into account the ethical issues like fairness, transparency, and perceptual biases. Finally, we analyse consists of identifying existing research gaps, the focus on the need to the regulatory adaptations and ethical considerations to comply with AI-driven pricing that creates the competitive and consumer-friendly online platform.

Keywords: AI Pricing, Online Platform, Tacit Collusion, Dynamic Pricing, Price Discrimination, Regulation

1. Introduction

The growing incorporation of artificial intelligence (AI) into the process of defining pricing on the internet led to a considerable evolution in the way online platforms have been relying on pricing strategies. Despite the increasing efficiency and profitability rates arising from AI statement pricing, they nevertheless give rise to questions regarding the fairness of the market, competition, and issue

DOI: 10.54254/2754-1169/2025.BJ24935

of underpinning consumer welfare [1]. The recent years have registered a success of introducing AI (Artificial Intelligence) in online business models, which have revolutionized the manner of fixing the price on the web. Its traditional pricing strategies in commerce were mainly those approaches that were fixed, such as cost-plus pricing, history-based pricing, and manual methods of market research, which helped to determine competitive prices [2]. These conventional ways are, without doubt, acknowledged in terms of their extensive use, but they usually lack the agility and flexibility that are so fundamental in the current ever-changing and data-intensive environment. The rapid growth of AI machine-learning (ML) technologies has made pricing increasingly automated, data-driven, and dynamic. The online platforms tend to take the same stance stemming from AI genomes and process data, which are real-time and let the platforms compute more real-time data that let the dynamic price be set and the data of users let the personalized price be set. AI-based pricing scheme further intensifies the competition in the digital marketplace [3] [4]. The human efficiency threshold learning makes better decisions in highly competitive environments while enhancing profit margins and realizing real-time as demonstrated in recent studies; AI tools are being more inseparably embedded in e-commerce and supply chain platforms to offer the competitive advantage through the deployment of the smarter pricing strategies [4][5].

However, these advancements also introduce complex challenges. Therefore, this article focuses on the nature of AI algorithmic pricing. One major key finding is the potential for algorithmic collusion, where pricing algorithms independently learn to coordinate with each other, raising prices without explicit agreements between firms, especially those based on reinforcement learning, are capable of sustaining collusive outcomes by adapting to market behavior. These mechanisms result in price synchronization and competition suppression, as demonstrated in real-world examples [6] [7]. Second, empirical studies show that algorithmic price discrimination is widely practiced on digital platforms. The listed types include location-based, purchase history-based, and device/OS-based, but they all add up to enormous amounts to pay for a single item. Subsequently, ethical questions such access closures, transparency, and consumer agency arise [8]. Third, Antitrust laws are out in favor of Traditionalists, and algorithmic collusion is challenging, particularly when self-learning AI detects price coordination without distinct human responsibility. Statute laws which address the "consensus" along with "intent" become more irrelevant. The enforcement is replaced by the accountability, opacity, and regulatory gap in the law. Professor Dupuy and other experts in the field are calling for changes that such as algorithm audits and new liability framework in order to adapt competition law to the AI era [9] [10]. Given this context, it is essential to understand both the economic impact and the regulatory implications of AI-driven pricing. While companies benefit from AI’s pricing power, policymakers face growing pressure to ensure that such technologies do not undermine competitive markets or exploit consumers. This study is thus significant for two key reasons: (1) It explores how autonomous learning in pricing algorithms can lead to unintended anti-competitive behavior; (2) It examines algorithmic price discrimination and the need for updated regulatory frameworks.

This literature review was conducted by searching academic databases such as Google Scholar and Elicit, focusing on AI and pricing algorithms studies. The following keywords were used in the search: “AI pricing algorithms,” “algorithmic collusion,” “AI pricing and consumers,” and “algorithmic pricing in online platforms.” Studies were selected based on their relevance to the economic aspects of AI in pricing strategies, with a focus on empirical research and theoretical contributions. Recent studies have been taken into account to a greater extent to guarantee that we receive the most fresh insights as well as a well-rounded understanding of the fast-changing area of AI-driven pricing. We categorized and evaluated the literature according to the themes of core economic theories (game theory and market structure), AI pricing mechanisms (autonomous collusion and reinforcement learning), industry cases, and regulatory challenges. In addition we critically analyzed the literature by combining the perspectives of different studies to identify research gaps and suggest future research directions.

This paper is structured as follows. Section 2 examines algorithmic collusion and market power, outlining key theoretical frameworks, including game theory and repeated games, to explain AI-driven collusion in oligopolistic markets. It then explores reinforcement learning as a mechanism for self-sustaining collusion, highlighting case studies and challenges in proving intent. The section concludes with an analysis of price synchronization and competition suppression. Section 3 investigates algorithmic price discrimination, detailing its mechanisms and empirical cases, including location-based, purchase history-based, and OS or device-based pricing. Ethical concerns are also discussed, particularly regarding fairness, consumer surplus, and trust. Section 4 addresses current regulatory challenges, comparing antitrust approaches across jurisdictions and examining policy implication and legal loopholes. Section 5 discusses research gaps, limitations, and future research directions in AI-driven pricing regulation and market dynamics. Section 6 concludes the conclusion of the research results.

2. Algorithmic collusion and market power

2.1. Key theories and frameworks

Game theory analyzes strategic decision-making among interdependent players. In repeated games, multiple interactions enable reputation-building, cooperation enforcement, and punishment of deviations. In the context of AI-driven pricing, repeated games help explain how intelligent agents develop collusive strategies through ongoing interactions. Unlike one-time games, where defection may be optimal, repeated interactions create incentives for cooperation, as AI agents recognize that short-term gains from undercutting competitors can lead to long-term losses if cooperation breaks down [11]. Methods like Tit-for-Tat, where parents respond to competition's previous choices, and Grim Trigger, where any disobedience leads to lifelong detention, allow AI pricing instruments to have sustainable collusion without formal words. AI pricing algorithms are empirically and theoretically examined. Reinforcement learning may improve these actions, and their responses change based on previous achievements [12]. The deduction of the prospect expense would be also a strong influence on the monitor of its competitor, which would help to encourage cooperative pricing, along with the AI agents who predict the probable behavioral patterns. These relationships are similar to human collusion in conventional markets, yet they are involuntary. Therefore, their implications for antitrust enforcement are overwhelming, to say the least [11].

In oligopolistic markets, the algorithms of AI pricing, such as Q-learning and particle swarm optimization, change the competition by increasing the speed of decision-making of the companies to autonomously adjust their prices to the market condition. These machines continuously train and adapt because the businesses realize the benefits of price stability instead of price warfare of veracity. The impact of AI-driven pricing depends on the market structure—whether modeled through Logit, Hotelling, or linear demand frameworks—which influences how firms compete [13]. In differentiated markets, AI may focus on maximizing individual firm profitability, while in more homogenous settings, algorithms may converge toward collusive-like behavior. As AI pricing becomes more prevalent, it challenges traditional competition models and complicates antitrust enforcement.

DOI: 10.54254/2754-1169/2025.BJ24935

3. Ai-driven tacit collusion

Based on the existing literature we get that AI first can reinforce learning to collude with itself in pricing. AI pricing algorithms utilize reinforcement learning to enable firms to form and maintain collusion without explicit coordination. Through trial-and-error learning, AI can identify and reinforce profit-maximizing pricing strategies, avoiding price wars and creating a stable pattern of high prices. Second, AI collusion produces price synchronization and competition suppression. The collusion of AI-driven pricing algorithms results in price synchronization, which suppresses competition and thus pushes up market prices. In particular, giving power to the algorithm to do the pricing automatically, the firms' pricing tends to coincide, which reduces price volatility and competitive pressure and ultimately leads to devaluation of consumer welfare. Besides that, AI's capabilities of real-time tracking further strengthen this synchronization effect, which makes firms react quickly to the strategies of their competitors in a way that sustains high-price levels [6].

3.1. Reinforcement learning and self-sustaining collusion

AI-driven pricing algorithms, particularly those utilizing reinforcement learning, have introduced a new aspect to the illegal collusion, which allows companies to adjust their pricing strategies independently as they respond to market conditions. Rather than traditional variations of collusion, which require verbal communication among firms, the new algorithms have the capabilities to process the competitors' current pricing strategies and market signals to dynamically adjust the prices for optimal benefit. As researchers display, trial-and-error learning is one of the approaches used by AI systems to determine and maintain the pricing strategies that yield the most revenue and further avoid coordination. During iterative learning, these codes are able to recognize the patterns that may lead to stable supra-competitive pricing, which allows them to support the collusive behavior without even the formal contract between companies. Furthermore, by introducing "punishing mechanisms" to deviate prices from this vertical-integration scheme, additional synergy arises [6]. Empirical evidence also supports these theoretical insights, being the results that [7] present from the German retail gasoline sector, which show that AI-hypersevery mechanism empowers firms with the ability to associate strategic moves in ways that guarantee the increasing profits even in competitive environments. The results show that other machine learning methods are not only reacting to the circumstances but also proactively shaping them in an attempt to maintain the integrity of competitive parity. Hence, if it wasn't for competitivity undercutting, machine learning would be able to adjust prices. This leading self-reinforcing system of price reshuffling gets firms into an environment where they collaboratively keep high-price levels, and thus the competition from new players will become more and more impossible [7].

In other words, the fact that AI can discover cooperative pricing without direct human-neural interplay has more effective implications for markets. Continuous interaction with the dynamic data of the market allows these algorithms to single out patterns that they use to reach optimal long-term performances without discovery. The experimental research explores that AI pricing tools not only adapt to the market conditions but also act as a deterrent to price competition and prompt firms with better price coordination. As per definitions and implications provided in [14], AI systems can utilize different learning approaches, including both asynchronous learning, which emphasizes previous actions solely, and synchronous learning, which augments previously learned features, allowing AI systems to improve their pricing strategies gradually through iterative learning. This adaptability serves the purpose of letting AI detect when market-driven pricing standards are being changed and implement corrective measures early on, allowing for the durability of price

DOI: 10.54254/2754-1169/2025.BJ24935

coordination [14]. This knowledge has been further buttressed by more recent findings in [8], which assert that AI's strength in fast adaptation amid market fluctuations fuels the sustainability of implicit collusion. Instead of the human intelligence process, which really has challenges to search the market data on real time, AI algorithms feasibly detect deviations of market pricing patterns and make the needed adjustments/decisions in real time. These measures manifest as punishment schemes, in the sense that firms temporarily lower their price below the market price in order to push community members to stop price competition. AI-based pricing mechanisms can implement the self-regulating type of collusion, revolving around firms continuously asserting their higher price levels without formal coordination among them.

3.2. Price synchronization and competition suppression

The emergence of AI-driven pricing solutions has led to a growing interdependence among firms regarding their pricing strategies, raising apprehensions over the effects of price synchronization on competition. Traditional price coordination requires explicit agreements, and unlike human mechanisms, algorithmic pricing systems are much more flexible and respond to competitors' moves, often causing collateral price cuts and subsequent price suppression while raising the price above the levels of perfect competition. The findings in [6] provide further explanation for the dynamic optimization of prices by reinforcement learning algorithms in response to market conditions, which can lead to tacit collusion. Among other things, applying various AI-driven strategies entails that firms' pricing algorithms become similar to each other and therefore act on the basis that pump up the price synchronization as well as lessen the price fluctuation and limits the competitiveness. Over time, this synchrony provides stabilization of prices, impoverishing consumer choice and, in the long run, it wouldn't be beneficial for consumers because of better price competition [15].

More so, the capacity of AI systems to gather market data in real-time further strengthens this effect, as the optimization becomes a function of the speed of response and the information it collects and processes. The self-learning nature similar to these algorithms also intensifies the price distortion, as the algorithms use that to enhance the pricing plans to maintain favorable price levels without overt coordination. Building on this, [16] highlight how algorithm-driven price changes affect market structure, noting that price synchronization influences both consumer behavior and firm performance. Besides, AI safeguards the ability of firms to conduct price uniformity, which reduces competition in price and promotes collusion among firms. Price collusion is an example of the kind of anti-competitive behavior that raises justifiable concerns about their negative impact on market competition, particularly with their ability to work without explicit agreements in place. Provision of supervision of trading algorithms is therefore needed, since algorithm pricing has the potential of collusion sustainability while maintaining its efficiency advantages [8].

3.3. Cases for AI collusion in pricing

3.3.1. Case 1: Amazon

Research indicates that up to 40% of algorithmic sellers have prices that exceed Amazon's prices, potentially due to accounting for the platform's commission fees. FThese notably include algorithmic pricing mechanisms finding themselves in exceptional circumstances where these instruments immoderately determine the prices of goods by the market due to unintended extreme hosts of pricing by these very automated systems [17]. In Amazon-based platforms, AI-driven

DOI: 10.54254/2754-1169/2025.BJ24935

collusive pricing describes a novel monster fostered by intelligent learning algorithms that leverage advanced pricing engine systems into the real-time pricing zone. These algorithms often lead to a scenario where sellers synchronize their pricing strategies, tending to elevate prices rather than fostering competition. This behavior can diminish competitive dynamics in the marketplace, as the algorithms may result in a more predictable pricing landscape where consumers face higher prices due to reduced price competition among sellers.

3.3.2. Case 2: German retail gasoline market

The paper analyzes the German retail gasoline market, highlighting unintentional AI-driven collusion following the 2017 adoption of algorithmic pricing software. This software allowed gas stations to swiftly adjust prices in response to competitors, resulting in pricing alignment. Data indicated that adopting stations saw a significant increase in profit margins compared to non-adopters, suggesting tacit collusion. The impact of algorithmic pricing varies across market structures. In non-monopoly markets, adoption leads to an average 9% increase in profit margins for adopting stations, indicating enhanced competitiveness. In duopoly markets, if only one station adopts the algorithm, market-level margins remain unchanged. However, when both stations adopt, margins increase by 28%, suggesting that mutual adoption fosters collusive behavior and higher prices. Overall, the effects of algorithmic pricing are more pronounced with dual adoption, creating a less competitive pricing environment [7].

3.3.3. Case 3: Uber

The Uber dynamic price system known as surge pricing is a little algorithm that increases FARE in real-time relatively to the fluctuating demand and supply in particular areas. To put it in simple terms, the authors suggest that this approach requires the partners to work more hours during peak period, as they are earning more favorably; due to this, an elasticity of about 0.15 to 0.17 is reflected. The adoption of the surge pricing above will not only set the stage for the existing drivers to extend their sessions to capture high earnings, but also urge synchronisation of price levels across the platform to mirroring current market conditions, which in itself leads to quality service delivery in the market. Due to this enhancing, a tacit collusion lies in the will of the Uber drivers as they are functioning towards the same goal, of maintaining or increasing their revenue [18]. This subsequently pushes the fare levels up during busy periods, lessens competition, and enhances Uber’s revenue model, resulting in more clients to Uber and a higher overall level of service.

4. Price discrimination and ethical concerns

4.1. The mechanism of algorithmic price discrimination

Algorithmic price discrimination (APD) is a phenomenon where an algorithm essentially determines the price for an individual customer by using their data to set a price. This form of price discrimination contrasts with the more common types of price discrimination: first-degree pricing (personalised pricing on the basis of knowing the consumer directly), second-degree pricing (offering quantity or product variations to self-select), and third-degree pricing (age or location as group characteristics). [19]—APD approaches mainly first-degree and third-degree discrimination by precisely estimating individual consumers' willingness-to-pay through continuous real-time data analysis [8]

DOI: 10.54254/2754-1169/2025.BJ24935

Artificial intelligence (AI), particularly machine learning (ML) methods, enables the practical implementation of APD. ML algorithms systematically analyse vast and diverse datasets—such as consumers' online browsing activities, transaction histories, location data, and technical device attributes—to identify subtle behavioural patterns and accurately predict consumer purchasing intentions. Through iterative learning, predictive modelling, and automated optimisation techniques, these AI systems dynamically refine price adjustments for individual consumers. [20] [21]

4.2. Empirical facts of APD in digital platforms

4.2.1. Location-based pricing

Location-based pricing is widely documented across various digital markets, revealing substantial price variations based on consumer geographic location and related technical settings. [22] analysed hotel booking platforms including Booking.com and Hrs.com, showing systematic geographic price differences. Specifically, users accessing from Germany and the United States consistently received lower prices compared to those from Pakistan or the Georgian Republic for identical hotel rooms. Additionally, technical factors such as browser language settings significantly affected prices. Changing the browser language setting from "en-US" to "de" resulted in average price variations of about 8.88%, while altering user-agent strings from Android to Windows caused price shifts averaging up to 17.33%. Further supporting these findings, the UK's Competition and Markets Authority [23] reported explicit geographic price disparities reaching as high as €167 for identical flights booked on Opodo simultaneously by consumers located in Austria versus Germany. [24] also documented explicit location-based pricing differences within countries, revealing price variations triggered by ZIP codes on several major e-commerce platforms in the United States. [25] contributed additional evidence of significant international price discrimination, showing that identical electronics and apparel products offered online exhibited average price differences of 20% to 40% across countries. Similarly, [26] analysed airline ticket pricing practices across European countries and identified that ticket prices frequently varied significantly, by more than 30%, depending purely on the European country from which the online booking websites were accessed.

4.2.2. Purchase history-based pricing

Purchase history significantly influences algorithmic price discrimination, as algorithms adapt product rankings and pricing based on consumers' past behaviours. [27] empirically demonstrated how personalised search rankings affect consumer click-through rates, with higher-ranked products gaining disproportionate attention regardless of actual price advantage. Additionally, [28] found explicit evidence on Amazon Marketplace, identifying 543 sellers (2.4%) using pricing algorithms to frequently match competitors' lowest prices (within $1 in 70% of cases). These sellers successfully secured the highly valuable Amazon Buy Box more often, directly enhancing sales performance.

Researchers quantitatively demonstrated how historical price-tracking influences algorithmic pricing decisions in e-commerce. Their study identified that about 10% of products listed by online retailers underwent daily price fluctuations explicitly informed by consumers' historical purchasing patterns. These adjustments ranged from minor (1%) to substantial (37%), averaging approximately 11% per price adjustment, indicating the significant influence of purchase histories on real-time personalised pricing strategies [29] . Using Netflix subscription data, [30] found that integrating detailed behavioural indicators—such as website visit frequency and browsing duration—enabled

DOI: 10.54254/2754-1169/2025.BJ24935

price discrimination that increased profits by approximately 12%, with some consumers paying nearly twice as much as others. Additionally, [31] experimentally demonstrated that dynamically framing prices based on historical consumer interactions improved perceived price fairness and boosted purchase intentions.

4.2.3. OS type/device-based pricing

Empirical evidence also extensively demonstrates algorithmic price discrimination based on operating systems (OS) and device types. Hannak et al. [24] studied pricing across 16 e-commerce platforms and found that nine exhibited clear device-specific pricing practices. Travelocity consistently offered approximately 15% cheaper hotel prices to iOS users compared to Android and desktop users. Similarly, Home Depot systematically directed mobile users towards higher-priced items, reflected by higher normalised discounted cumulative gain (nDCG) metrics compared to desktop users. Notably, Android users were presented with fewer search results (24) than iOS users (48), with nearly zero overlap between the products listed for each group.

Frequent and substantial price variations driven by device and OS characteristics have been explicitly documented in recent studies [29]. It was found that algorithm-induced price volatility could have major intra-day correlations, with prices of around 10% of items sold by U.S. online retailers changing rapidly throughout the day—ranging from 1% to as high as 37%. These dynamic adjustments are often unpredictable and substantial, with a median absolute price change of about 11% per adjustment.

4.3. Ethical concerns

4.3.1. Fairness

With the rise of data linked to consumers, brands may advance their precise aiming to consumer groups and individuals. However, this could result in some consumer groups. Similar to the problems facing minorities and vulnerable groups, having unequal treatment or abuse on the basis of: gender, ethnicity, education level, wealth status, or madness [32].

Personalized pricing between people is viewed as unjust, while price disparities between shops or sales channels are largely acceptable throughout a large body of consumer research [33]. Discounts offered to regular or new customers are generally viewed as less reasonable than price depending on purchase timing, such as early access or off-peak discounts [34]. Group-buying methods and auction-based pricing are thought to be more equitable than individual-specific pricing tactics [35] [36]. About two-thirds of consumers have a positive opinion of volume-based discounts, while customer profile–based pricing strategies were the least known and rejected by over half of consumers [37]. Purchase quantity-based pricing was regarded as the most equitable, followed by time- and loyalty-based pricing, whereas channel-based and geographically varied pricing were considered the least equitable [38]. Similarly, group/status-based pricing was widely acceptable, but residence-based pricing was viewed as especially unfair [39].

Consumers favor pricing methods that feel merit-based (such as timing or quantity) over those based on ambiguous criteria or personal identification, according to the unifying theme among these studies.

4.3.2. Consumer surplus

Both favorable and unfavorable effects on consumer surplus might result from algorithmic pricing. Positively, individualized pricing may draw in bargain-hunting customers, especially if it offers perceived benefits like better service or higher-quality products [40]. Price-conscious buyers may also profit from dynamic pricing, which offers decreased costs in return for less features, later purchase dates, or patience. These advantages are not dispersed equally, though. Algorithms that are primarily utilized for profit maximization have the ability to reduce the excess of inelastic consumers by extracting greater prices from them. The degree to which the pricing approach appears straightforward and value-enhancing will determine whether or not consumers gain. Even reduced rates in other categories won't make up for the decline in customer satisfaction and trust if they believe they are being singled out and charged extra without cause [40].

4.3.3. Trust

For algorithmic pricing solutions to be successful, consumer trust is essential. There is a considerable decline in willingness to buy when prices are viewed as unfair and personally unpleasant. Lack of transparency exacerbates this effect by leaving customers in the dark about why they are paying a specific price. Because of this, some customers try to get lower "new user" fees by manipulating the system by setting cookies, utilizing incognito browsers, or making fictitious accounts. These actions show that customers actively try to undermine algorithmic pricing in addition to viewing it as unreliable. The long-term relationship between a company and its customers is jeopardized when trust is lost. Customers start to view businesses as opportunistic rather than customer-focused, which can harm public impression and brand loyalty, especially for big platforms that use dynamic pricing extensively. [41]

5. Regulatory challenges and antitrust law

5.1. Challenges under current antitrust regulations

The application of antitrust law to algorithm-driven markets reveals a deep mismatch between traditional legal assumptions and evolving technological realities. Competition law has long depended on identifying human intent, explicit agreements, or dominance abuse. Yet, modern pricing algorithms—especially those using machine learning—can autonomously replicate collusive outcomes without communication or oversight, challenging the foundational requirement of a “meeting of minds”[42] [10]

Legal attribution is one major obstacle. Although Commissioner Vestager affirms that firms remain accountable for their algorithms, assigning responsibility becomes difficult when outcomes result from opaque, self-learning systems [10]. Algorithms can adjust behavior solely through market signals, producing parallel conduct that technically falls outside Article 101 TFEU. Scholars like Kaplow [43] highlight how digital environments blur the line between legitimate mimicry and coordination, while still harming consumers comparably to explicit cartels.

Enforcement limitations further complicate regulation. Traditional frameworks presume static human-devised strategies, but autonomous agents may evolve collusive behaviour independently. As Calvano et al. [6] demonstrate, even simple Q-learning algorithms can sustain supra-competitive pricing without instructions. In such cases, firms may deny intent, resulting in a “liability vacuum” [10].

Finally, regulatory lag undermines effective oversight. While financial and data protection regimes have introduced real-time testing and transparency audits (e.g., GDPR, MiFID II), competition law remains reactive and ill-suited to fast-evolving algorithmic systems [9]. Calls for reform—including Scherer's [44] proposal for algorithm certification—reflect growing concern that enforcement tools are falling behind. Meanwhile, global digital platforms like Amazon extend algorithmic coordination across markets and actors, often in ways that escape existing definitions of horizontal or vertical restraints [45].

5.2. Legal loopholes and policy implications

5.2.1. Difficulties in proving intent and liability in AI-driven tacit collusion

The growing autonomy of AI pricing algorithms complicates the attribution of legal liability when anti-competitive behavior arises. While algorithms are technically tools created and deployed by humans, their ability to self-learn and make independent decisions makes it difficult to establish clear lines of responsibility. Mehra outlines three potential approaches: assigning liability to the algorithm itself, to the human operator or programmer, or to no one — an outcome broadly viewed as unacceptable [46]. EU Commissioner Vestager has stressed that firms cannot shield themselves from legal accountability by claiming that algorithms operate independently, reiterating the necessity of maintaining human responsibility even in complex automated environments [47]. This issue is particularly urgent when AI systems learn to collude through trial and error rather than explicit instruction, revealing the limitations of legal frameworks based on provable intent and human control. As algorithms increasingly shape market outcomes autonomously, current approaches to liability are strained and in need of reassessment [48].

5.2.2. Limitations of existing antitrust laws in addressing non-explicit agreements

One of the main obstacles to regulating algorithmic pricing is the outdated legal definition of "agreement." The idea of a "meeting of minds," typically achieved through interpersonal communication or formal contracts, remains central to traditional antitrust law [48]. However, algorithms can now reach pricing convergence through fast, reactive interactions—responding to shared market signals or similar training data—without any explicit coordination. As argued in previous research [46][49], the distinction between lawful parallel conduct and illegal collusion becomes blurred when algorithmic responses occur faster than human cognition can track. This challenge is compounded by the fact that modern AI systems can learn to coordinate prices through trial and error, even without being programmed to communicate. Because such behavior mimics collusion without direct contact, current legal frameworks often fail to detect or address these outcomes, revealing a growing mismatch between how markets function algorithmically and how antitrust law defines "agreement."

5.2.3. Risk of regulatory lag

While AI technologies continue to evolve at a rapid pace, regulatory frameworks—particularly in competition law—have not kept up. Sectors like finance and data protection have introduced robust mechanisms such as MiFID II, GDPR, and RTS 6/7, incorporating risk assessments, algorithm testing, and real-time monitoring [50]. In contrast, antitrust enforcement remains reactive, lacking proactive tools to anticipate or preempt harmful algorithmic behavior. Complex, proprietary algorithms used in dynamic pricing and ad targeting increasingly operate in regulatory blind spots. A proposal for an Artificial Intelligence Development Act (AIDA) highlights the need for bespoke legal frameworks that reflect the unique risks posed by black-box AI systems [44]. Without timely intervention, the regulatory lag between technological innovation and legal oversight will allow firms to exploit algorithmic strategies that undermine competition, while remaining legally unaccountable.

5.2.4. Potential reforms and new enforcement mechanisms

Scholars and politicians have suggested several modifications to strengthen enforcement mechanisms in order to overcome the deficiencies of the current competition law in algorithm-driven markets. To enable authorities to promptly address indications of collusion, implementation of algorithm compliance programs, ex-ante testing, and notice-and-take-down processes have been supported [42]. Additional suggestions include mandatory algorithmic design documentation, transparency requirements, and the creation of "kill switches" or override procedures to stop detrimental behavior. Furthermore, institutional reforms such as algorithm certification systems based on liability tiers and the establishment of independent international digital regulators have been highlighted as necessary [48].

By attempting to manage risks proactively rather than responding after the fact to consumer harm, these strategies represent a larger move toward preventative regulation. Ultimately, ensuring that algorithmic innovation supports, rather than undermines, market competition will require a coordinated mix of legal reform, interdisciplinary oversight, and international cooperation.

6. Discussion

As this present research explores the part of the subtle collusion component of AI algorithmic pricing and the effect of price discrimination on consumers, as well as regulatory challenges, thorough consideration is needed. Although the findings provide valuable insights, the study identifies the fact that there are key gaps that require further research.

The theoretical models developed in this research, guided by AI algorithmic pricing, have a significant drawback, namely the programmatic market assumptions on which they are built. These theories overlook the intricacies that occur in real-life markets, where firms deal with sustained demand or cost shocks, reshaping of market structures, and other uncertainties. It has been noted that in actual business environments, companies may also deal with external variables like changes in regulation or transformations in customer preferences that influence the relationships among collusion algorithms. This gap is most likely to be closed when future researchers include those elements, namely through implementing random variables and more complex market dynamics [6].

Moreover, one of the reasons cited in studies in this area is that they tend to focus on the medium-term and long-term effects of pricing strategies and customer responses. They do not fully capture market flows and shifts in consumer behavior over time [22][29]. However, these studies usually fail to consider long-term changes in the market environment and consumer behavior. Consumer preferences and purchasing habits may change over time, which may affect the effectiveness of algorithmic pricing. It has been pointed out that although machine learning algorithms can continually optimize pricing strategies with real-time data, their ability to adapt to long-term trends remains unclear [8]. Future research should consider long-term data to analyze cyclical changes in the market, fluctuations in consumer demand, and the long-term effects of price discrimination strategies to better understand the persistence and changing trends of algorithmic pricing.

DOI: 10.54254/2754-1169/2025.BJ24935

Third, the development of existing literature on regulatory obstacles and antitrust enforcement still falls far behind. While researchers have advocated the divergence between current legal frameworks and fast-paced technological developments, there has been little deliberation on whether instant close monitoring and more flexible, revisable antitrust regulations will be enforced as algorithmic practices continue evolving rapidly [42][10]. This leaves legislators grappling with a crucial question: how can they create antitrust laws that not only prevent facilitating algorithmic collusion but also preserve the efficiency benefits of algorithmic pricing?

The upcoming studies should take on multiple shortcomings in the current literature on AI algorithmic pricing and its implications on consumers and regulatory frameworks. Firstly, the current theoretical models of the market mainly depend on programmatic market assumptions, which ignore market complexities, such as constant demand or cost variances, marketplace structures fluctuations, and externalities, like regulations or consumer preferences. Expanding the model to include stochastic variables and a simulated market environment with dynamic conditions would be more reflective of algorithmic collusion in practice. Lastly, most studies analyze short-term algorithmic pricing strategies and customers' responses, whereas its long-term implications on customers should be investigated as well. Human behavior and surroundings equally change, hence the need to look into how these AI algorithms track and manage long-term trends as well as cyclical demand changes. In addition, the literature on regulatory challenges is still evolving slowly. Further studies can focus on how manufacturers can be granted more agile antitrust regulations that enforce real-time supervision and deter potential AI collusion while still preserving the algorithms-based efficiency principles. It is also essential to think about algorithmic price discrimination impacts on social settings and fairness of consumer groups because algorithms might increase inequality among social classes. On top of that, however, the aspect of cross-platform pricing patterns and the implication of regulation are too less investigated areas, given the fact that several platforms may price their products together and also pose the same harm to competition, according to a recent study. Consumer attitudes toward algorithmic pricing from an ethics perspective is a broad area of study, particularly focusing on its influence on customer confidence and their readiness to cooperate with online providers. Future studies can help to close the gap by better understanding algorithmic pricing, long-term impacts, and the associated regulatory frameworks of fairness and competitiveness.

7. Conclusion

Following this literature review, the study has been carried out in the context of the pricing algorithms by AI in online platforms, while it examined their role in the loss of market power, the occurrence of tacit collusion, price regulation, and the occurrence of regulatory obstacle. Fair AI-enabled pricing offers dynamic, real-time adjustment that lets firms tacitly collude and keep a certain level of cooperativeness. While automated price discrimination can augment price efficiency, it simultaneously evokes ethical queries about parity, customer surplus, and confidence. Besides, the regulatory surrounding is ill-devised and dysfunctional, with existing laws targeting the antitrust structure incompletely fitting for the accelerated development of AI. The call for future research will include investigating these gaps in greater detail, refining interventions through an increased understanding of efficiencies over time and markets and revisiting areas such as consumer behavior and regulatory frameworks that need to be more adaptable to balance innovation with consumers' protection.

Acknowledgments

Lixun Song, Changhao Chen and Federick Lin contributed equally to this work and should be considered co-first authors.

Lixun Song was responsible for the ABSTRACT, INTRODUCTION, ALGORITHMIC COLLUSION AND MARKET POWER, DISCUSSION and CONCLUSION.

Changhao Chen and Federick Lin were responsible for the PRICE DISCRIMINATION AND ETHICAL CONCERNS and REGULATORY CHALLENGES AND ANTITRUST LAW .

The contribution of all authors to the developing paper is indubitable. For all authors, the content discussed, constructive comments given, and acceptance of the final version of the manuscript by all the involved authors is the goal.

References

[1] Dorner, F.E. (2021). Algorithmic collusion: A critical review. arXiv: 2110.04740 [cs]. [online] Available at: https: //arxiv.org/abs/2110.04740.
[2] M. Masyhuri, pricing strategies application amongst the top e-commerce southeast asian countries". Asian Journal of Management Analytics, vol. 2, no. 4, 2023, p. 379-390. DOI: https: //doi.org/10.55927/ajma.v2i4.6068
[3] Sodiya, E., Umoga, U., Amoo, O., & Atadoga, A. (2024). ai-driven warehouse automation: a comprehensive review of systems. GSC Advanced Research and Reviews, 18(2), 272-282. DOI: https: //doi.org/10.30574/gscarr.2024.18.2.0063
[4] Muthaluri, J. (2024). Optimizing supply chain management and marketing strategies: ai and ml integration for competitive advantage. EATP, 8990-8997. DOI: https: //doi.org/10.53555/kuey.v30i5.4494
[5] Erdmann, A., Yazdani, M., Iglesias, J., & Palacios, C. (2024). pricing powered by artificial intelligence: an assessment model for the sustainable implementation of ai supported price functions. Informatica, 529-556. https: //doi.org/10.15388/24-infor559
[6] Calvano E, Calzolari G, Denicolo V, et al. Artificial intelligence, algorithmic pricing, and collusion [J]. American Economic Review, 2020, 110(10): 3267-3297.
[7] Assad S, Clark R, Ershov D, et al. Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market [J]. Journal of Political Economy, 2024, 132(3): 723-771.
[8] Gautier, A., Ittoo, A., & Van Cleynenbreugel, P. (2020). AI algorithms, price discrimination and collusion: a technological, economic and legal perspective. European Journal of Law and Economics, 50(3), 405-435.
[9] Mackay, A., & Weinstein, S. N. (2022). Dynamic pricing algorithms, consumer harm, and regulatory response. Washington University Law Review, 100(1), 111–173.
[10] Mehra, S. K. (2021). Price discrimination-driven algorithmic collusion: Platforms for durable cartels. Stanford Journal of Law, Business & Finance, 26.
[11] Game Theory and Repeated Interactions Rhodes, Andrew, and Jidong Zhou. "Personalized pricing and competition." American Economic Review 114.7 (2024): 2141-2170.
[12] Han, T. A., Perret, C., & Powers, S. T. (2021). When to (or not to) trust intelligent machines: Insights from an evolutionary game theory analysis of trust in repeated games. Cognitive Systems Research, 68, 111-124.
[13] Sanchez-Cartas, J. M., & Katsamakas, E. (2022). Artificial intelligence, algorithmic competition and market structures. IEEE Access, 10, 10575-10584.
[14] Asker, J., Fershtman, C., & Pakes, A. (2021). Artificial intelligence and pricing: The impact of algorithm design (No. w28535). National Bureau of Economic Research.
[15] Williams, Cole, and Anastasiia Parakhoniak. "Popularity or Price: Which Should Determine the Display of Top Firms?." Available at SSRN (2024).
[16] Johnson, Justin P., Andrew Rhodes, and Matthijs Wildenbeest. "Platform design when sellers use pricing algorithms." Econometrica 91.5 (2023): 1841-1879.
[17] Monden, Y. (2020). Pricing Strategy and Cost Compensation of the Platforms of a Two-sided Market—With a Case Study of Amazon Online Shopping. In Sustainability Management And Business Strategy In Asia (pp. 189-201).
[18] Chen, M. K., & Sheldon, M. (2016). Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform. Ec, 16, 455.
[19] Belleflamme, P., & Peitz, M. (2015). Industrial organization: Markets and strategies (2nd ed.). Cambridge University Press.

DOI: 10.54254/2754-1169/2025.BJ24935

[20] Dubé, J.-P., & Misra, S. (2021). Personalized pricing and consumer welfare (NBER Working Paper No. 23775). National Bureau of Economic Research.
[21] Seele, P., Dierksmeier, C., Hofstetter, R., & Schultz, M. D. (2021). Mapping the ethicality of algorithmic pricing: A review of dynamic and personalized pricing. Journal of Business Ethics, 170(4), 697–719.
[22] Hupperich, T., Tatang, D., Wilkop, N., & Holz, T. (2018). An empirical study on online price differentiation. In Proceedings of the Eighth ACM Conference on Data and Application Security and Privacy (pp. 76–83). ACM. https: //doi.org/10.1145/3176258.3176312
[23] Competition and Markets Authority (CMA). (2018). Pricing algorithms. Retrieved from https: //assets.publishing.service.gov.uk/media/5bbb2384ed915d238f9cc2e7/Algorithms_econ_report.pdf
[24] Hannak, A., Soeller, G., Lazer, D., Mislove, A., & Wilson, C. (2014). Measuring price discrimination and steering on e-commerce websites. In Proceedings of the 2014 Conference on Internet Measurement Conference (pp. 305–318
[25] Cavallo, A. (2018). More Amazon effects: online competition and pricing behaviors (No. w25138). National Bureau of Economic Research.
[26] Mikians, J., Gyarmati, L., Erramilli, V., & Laoutaris, N. (2012). Detecting price and search discrimination on the Internet. In Proceedings of the 11th ACM Workshop on Hot Topics in Networks (pp. 79–84).
[27] Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. Management Science, 55(10), 1605–1622.
[28] Chen, L., Mislove, A., & Wilson, C. (2016). An empirical analysis of algorithmic pricing on Amazon Marketplace. In Proceedings of the 25th International Conference on World Wide Web (pp. 1339–1349).
[29] Vomberg, A., Homburg, C., & Sarantopoulos, P. (2024). Algorithmic pricing: Effects on consumer trust and price search. International Journal of Research in Marketing.
[30] Shiller, B. R. (2013). First degree price discrimination using big data (p. 32). Brandeis Univ., Department of Economics.
[31] Weisstein, F. L., Monroe, K. B., & Kukar-Kinney, M. (2013). Effects of price framing on consumers' perceptions of online dynamic pricing practices. Journal of the Academy of Marketing Science, 41, 501-514.
[32] Priester, Anna; Robbert, Thomas; Roth, Stefan (2020) : A special price just for you: effects of personalized dynamic pricing on consumer fairness perceptions, Journal of Revenue and Pricing Management, ISSN 1477-657X, Palgrave Macmillan UK, London, Vol. 19, Iss. 2, pp. 99-112, https: //doi.org/10.1057/s41272-019-00224-3
[33] Garbarino, E., and S. Maxwell. 2010. Consumer response to norm- breaking pricing events in e-commerce. Journal of Business Research 63 (9/10): 1066–1072.
[34] Grewal, D., D.M. Hardesty, and G.R. Iyer. 2004. The effects of buyer identification and purchase timing on consumers' perceptions of trust, price fairness, and repurchase intentions. Journal of Interactive Marketing 18 (4): 87–100.
[35] Haws, K. L., & Bearden, W. O. (2006). Dynamic pricing and consumer fairness perceptions. Journal of consumer research, 33(3), 304-311.
[36] Huang, J.H., C.T. Chang, and C.Y.H. Chen. 2005. Perceived fairness of pricing on the internet. Journal of Economic Psychology 26 (3): 343–361.
[37] Krämer, A., M. Friesen, and T. Shelton. 2018. Are airline passengers ready for personalized dynamic pricing? A study of German con- sumers. Journal of Revenue and Pricing Management 17 (2): 115–120.
[38] Lii, Y.S., and E. Sy. 2009. Internet differential pricing: Effects on consumer price perception, emotions, and behavioral responses. Computers in Human Behavior 25 (3): 770–777.
[39] Wu, C.C., Y.F. Liu, Y.J. Chen, and C.J. Wang. 2012. Consumer responses to price discrimination: Discriminating bases, inequal- ity status, and information disclosure timing influences. Journal of Business Research 65 (1): 106–116.
[40] Choe, P., & Wu, J. (2015). Customer perceptions toward dynamic pricing for wireless data service. International Journal of Mobile Communications, 13(2), 172. https: //doi.org/10.1504/ IJMC.2015.067962.
[41] Gerlick, J.A., Liozu, S.M. Ethical and legal considerations of artificial intelligence and algorithmic decision-making in personalized pricing. J Revenue Pricing Manag 19, 85–98 (2020). https: //doi.org/10.1057/s41272-019-00225-2
[42] Ezrachi, A. and M. E. Stucke (2016), "Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy", Harvard University Press, United States.
[43] Kaplow, L. (2011). On the meaning of horizontal agreements in competition law. California Law Review, 99(3), 683–818.
[44] Scherer, M. U. (2016). Regulating artificial intelligence systems: Risks, challenges, competencies, and strategies. Harvard Journal of Law & Technology, 29(2), 353–400.

DOI: 10.54254/2754-1169/2025.BJ24935

[45] Townley, C., Morrison, E., & Yeung, K. (2017). Big data and personalized price discrimination in EU competition law. King's College London Law School Research Paper No. 2017-38.
[46] Mehra, S. K. (2015), "Antitrust and the Robo-Seller: Competition in the Time of Algorithms", Minnesota. Law Review, Vol. 100, www.minnesotalawreview.org/wp-content/uploads/2016/04/Mehra_ONLINEPDF1.pdf.
[47] Vestager, M. (2017), "Algorithms and Competition", Speech at the Bundeskartellamt 18th Conference on Competition, Berlin, https: //ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/bundeskartellamt-18th-conference-competition-berlin-16-march-2017_en.
[48] OECD (2017). Algorithms and Collusion: Competition Policy in the Digital Age. https: //www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm
[49] Borenstein, S. (1999), "Rapid Price Communication and Coordination: The Airline Tariff Publishing Case", in J. E. Kwoka Jr. and L. J. White (Eds.), The Antitrust Revolution: Economics, Competition and Policy, Oxford University Press, New York, pp. 310-328, http: //global.oup.com/us/companion.websites/fdscontent/uscompanion/us/pdf/kwoka/9780195322972_09.pdf.
[50] European Securities and Markets Authority (ESMA). (2021). MiFID II review report on algorithmic trading (ESMA70-156-4572). https: //www.esma.europa.eu/sites/default/files/library/esma70-156-4572_mifid_ii_final_report_on_algorithmic_trading.pdf