Dynamic Pricing: The Functionality of Interactive Pricing Models

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Artificial intelligence (AI) offers unprecedented opportunities for businesses to personalize their interactions with potential customers. AI personalization—the application of machine learning algorithms to customize user experiences—is transforming how institutions engage with consumers across sectors. Recent surveys indicate that 60% of consumers desire AI applications for shopping experiences, while 71% expect companies to deliver personalized content[1]. Modern dynamic pricing leverages artificial intelligence to adjust prices in response to fluctuating market conditions, and represents one of the most consequential forms of AI personalization in the commercial sphere. In *Prediction Machines*, authors Agrawal, Gans, and Goldfarb demonstrate that advances in AI lower the cost of prediction and decouple prediction and judgment [2], while its powerful predictive capabilities enable the optimization of inventory levels, reduce stockouts, minimize overstock situations, and enhance supply chain efficiency [3]. An inherent ability to lower costs makes artificial intelligence economically significant, enabling businesses to adopt new production strategies that would previously have been viewed as uneconomical. Many of the responsibilities that occupy human employees' time, including automat[ing] online processes and increasing the precision of estimates in mathematical calculations; it is dually seen as a tool that can be used to further strengthen the relationships between a business and its customers, offering customized marketing, product recommendations, and tailored customer service solutions, drawing on customers' online data to offer them a tailored experience, and even monitoring customers' discussions of a product online to conduct sentiment analysis are now delegated to AI systems. This new technology plays an instrumental role in business and beyond, improving both the accuracy and cost-effectiveness of prediction.

Government agencies, including the Federal Trade Commission in the United States and regulatory bodies within the European Union have expressed concerns that such algorithmic pricing might facilitate discrimination against vulnerable consumer groups or potentially undermine competition through tacit collusion among competing algorithms. Our investigation into dynamic pricing and its regulatory landscape reveals nuanced impacts on consumers: some benefit from lower prices tailored to their price

[1] See IBM, 2024; Mckenzie, 2021 for more context on personalized content delivery.
[2] Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence.* Harvard Business Review Press.
[3] Bombalier, J. (2024). The Competitive Advantage of Using AI in Business. Florida International University.

sensitivity, while others face higher costs based on their demonstrated willingness to pay. The effect on market competition remains inconclusive, with empirical studies showing algorithmic sellers achieving greater marketplace visibility and sales volumes, yet raising questions about long-term market health and transparency. The purpose, and primary academic function of this paper is to understand the economic repercussions of AI-based dynamic pricing, and how they affect both consumption behavior and competitive conditions.

Dynamic Pricing in Theory

The foundation of dynamic pricing lies, evidently, in the foundational economic concept of *price elasticity*, which measures how consumers change their purchases in response to price changes. The price elasticity of demand sets the boundaries for dynamic pricing, limiting how far prices can move up or down before consumer responses make such moves unprofitable. With dynamic pricing, algorithms use past and current data to quickly decide the optimal prices for maximizing profits. Identifying which products' prices can fluctuate while maintaining demand — and which cannot — is the first key component of this process : calculating, and then applying this price elasticity data is the second, crucial step to the success of this strategy.

Through this process, the well-known supply and demand equilibrium is achieved by quickly choosing prices that equate the quantities that customers are willing to buy with those that the producers are willing to supply. This is differentiated from the typical supply and demand, where the prices do not fluctuate automatically or in real time, revealing infinitely more instances of surplus and shortages. The market is constantly balanced in our new real-time pricing supply and demand equilibrium, with no over- or under-production. The fluctuating market price in the forces of supply and demand all perfectly balanced each other out in real-time, something that was never perceived as possible in the supply chain world until the introduction of AI, allowing for mass amounts of data to be analyzed and calculated to produce accurate decisions based on data. Dynamic pricing can initially seem like an efficient approach for managing the demand side of the classic supply-and-demand equation, typically aimed to reduce what is known as a peak-to-average ratio, creating an equilibrium between a

producer's ability to supply a good and the consumer's demand[4]. Typically, this works systematically and predictably with AI dynamic pricing algorithms: if the demand for a product the firm produces increases, the algorithm will sense this increase and suggest a corresponding increase in price. Not only does raising the price help calm the demand increase, but it also provides an incentive for sellers to provide more products into the supply while also discouraging consumers from buying too much. This would bring the market back to equilibrium. If demand were to decrease, the algorithm again senses the shift in consumer preferences, and would suggest a decreased price to encourage an increase in demand and prevent suppliers from overproducing, resulting in a surplus.

Access to real-time data on supply and demand enables a more efficient market, as firms can dynamically adjust outputs based on immediate feedback from market conditions. The key consideration in implementing dynamic pricing strategies is the potential to maximize profit margins by adjusting prices in response to changing market conditions or individual consumer behavior. However — if consumers perceive pricing practices as unfair or excessively variable, particularly when similar products are offered at different prices to different individuals, customer trust and loyalty may be undermined. In such cases, this AI-powered technology assumes an equation of its own: how much can you maximize profits through dynamic pricing before consumers discard their demand?

A study examining dynamic pricing and how consumers influence the development of these strategies[5] found that loss aversion is a powerful force in driving consumer decision-making. Loss aversion in this context is an inherent cognitive bias where a consumer begins to feel the pain of an increase in price more than the feelings of pleasure associated with receiving a discount of the same magnitude. Often, dynamic pricing models, which are commonly used in fields such as transportation, airlines, and in many cases, the retail industry, adjust their prices on a dynamic basis that, in a way, attempts to minimize this cognitive discomfort associated with what the consumers feel is a loss.

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[4] In economics, the peak-to-average ratio (PAR) is a measure of how much the highest point of a variable (like demand) deviates from its average value.

[5] Akram, R., Jadoon, I. A., Shah, S. M. M., & Heider, B. (2021). *Exploring consumer perception and behavior towards dynamic pricing*. Business Management and Finance Open Review, 1(1).

To understand dynamic pricing, it's essential to first consider pricing without it. In a static pricing model, a supplier sets a single price for all customers. For example, if there are two types of customers, H and L, with H willing to pay more than L, the supplier must choose a price that only H is willing to pay or includes both H and L at a lower price. This decision is influenced by the business's costs and the relative willingness to pay (WTP) of each customer type. Dynamic pricing allows the supplier to set different prices for H and L, maximizing profits by charging each customer type their respective WTP. Without dynamic pricing, a firm might not be able to afford changing a single price that both H and L would be willing to pay. This approach enables AI to identify customer segments and adjust prices in real-time, ensuring that the supplier can capture the maximum possible revenue from each transaction.This behavior can impact competitive dynamics; for example, firms must carefully balance price adjustments to avoid triggering price wars while still capturing maximum value. In monopolistic markets, the lack of competition allows for more aggressive dynamic pricing strategies.

The effects of rivalry in dynamic pricing are often overlooked. Competitors' reactions to price changes can influence market dynamics, as firms consider potential competitive responses when implementing dynamic pricing strategies. Implementing a strategy such as dynamic pricing, when done correctly and avoiding customer dissatisfaction, can result in increased profitability for a firm, allowing businesses to identify which customers will pay which prices for their goods. They can target consumers who will pay more and charge higher prices while closing price gaps across other products. Having an algorithm that, in real-time, changes prices to most accurately reflect supply and demand while also taking into account price elasticity will ultimately result in some financial gains. Some reports indicate that firms adopting a dynamic pricing model experience an average sales increase of up to 15%, highlighting the strategy's potential to automate pricing, stimulate customer demand, and maximize revenue. Sales figures are not the only performance metric that can benefit from dynamic pricing. One study cited that overall profitability can increase by approximately 10% when prices are adjusted in real time to reflect demand.[6] In terms of general revenue changes resulting from dynamic pricing, McKinsey found that firms using this strategy saw revenue increases of 2–5%[7], which most firms found covered the

[6] Quaxar. (2023, October 24). *Dynamic pricing: Revenue increment through price optimization*. LinkedIn.
[7] McKinsey & Company. (2024). *How retailers can drive profitable growth through dynamic pricing.*

initial costs of setting up the model and integrating it into the business internally. The flexibility provided by this pricing style allowed businesses to maximize revenue during heightened demand and reduce prices accordingly when demand slows: this ability to rapidly adjust prices based on current market situations is one of the key drivers behind the initial successes seen by dynamic pricing.

The return on investment remains a primary metric when discussing the relevant economic and financial contexts of implementing dynamic pricing. Does incorporating a dynamic pricing algorithm, most likely using AI, provide enough return to justify the initial significant infrastructure investment and the potential risk of decreased demand or customer dissatisfaction? There are possible hard returns for AI implementation regarding time saved and productivity levels increasing, along with potential cost savings from a labor standpoint: the soft return on investment in AI looks more like increased skill retention, better customer experiences, and improved overall business adaptability. Operational costs are associated with updating a firm's current pricing strategy from manual and static to AI-algorithmic and constantly changing, including initial and perpetual data collection, storage, and analysis, as well as ongoing model updating, initial development, and system maintenance. Additionally, firms must invest in integrating AI with their existing infrastructure, ensuring compatibility with inventory management, customer relationship management (CRM), and sales platforms. Training personnel to interpret and respond to AI-driven pricing insights also presents both a financial and operational challenge. Despite these costs, the long-term benefits of AI-based pricing—such as improved price accuracy, real-time adaptability, and increased profit margins—can outweigh the initial investments, especially when deployed at scale. Of course, the technological infrastructure needed to install and implement such a substantial pricing-altering strategy in real-time with accurate results requires extreme and resilient computing power and various cloud services.[8] These factors can vary and significantly impact the various operating costs depending on limitations and requirements such as the complexity and scale of implementation within the firm itself. And, while dynamic pricing can generate measurable gains in efficiency and profitability, it also raises various concerns about firm behavior—especially when rival companies deploy algorithms that respond to one another's price signals in real time. A prominent example of this tension between

[8] LeewayHertz. (2023). *AI-powered dynamic pricing solution*.

innovation and antitrust scrutiny emerged in the case of Amazon's "Project Nessie." In late 2023, the Federal Trade Commission (FTC), joined by 17 states, filed a lawsuit alleging that Amazon employed a secret AI-powered pricing algorithm—codenamed "Project Nessie"—to test the limits of price increases while expecting competitors to follow suit. According to the FTC's complaint, this strategy allegedly generated over $1 billion in additional revenue before the tool was discontinued in 2019. Although Amazon contends that Project Nessie was intended solely to prevent unsustainably low pricing and was scrapped years ago.

A study by Singh, et al[9]. distinguishes between simple rule-based pricing—such as fixed price-matching—and more sophisticated reinforcement learning (RL) algorithms, showing that RL systems can exploit the predictable, reactive behavior of simpler models. As a result, this interaction may lead to a cascade of price increases that resemble implicit collusion, even in the absence of any explicit communication between firms. The FTC's increased scrutiny of Amazon's practices reflects these concerns, highlighting the regulatory challenges in addressing potential anti-competitive outcomes in an era of AI-driven pricing. Key findings from the CMU study include tit-for-tat pricing dynamics, where simple rule-based algorithms tend to mirror competitors' price changes, leading to a cascading effect where price increases are amplified across the market. When AI-powered RL algorithms compete against these simpler pricing models, they learn to exploit this reactive behavior—raising prices strategically to trigger higher price points across the entire market. Additionally, unlike traditional price-fixing schemes where firms communicate to set high prices, AI-driven algorithmic pricing does not require explicit coordination. The FTC's challenge in regulating algorithms lies in proving that they constitute anti-competitive behavior despite lacking direct agreements between firms.[10] The implications for consumers can be significant, as the Singh et al. study warns that AI pricing strategies may reduce consumer surplus, leading to higher overall market prices without any formal collusion. This raises concerns for antitrust regulators, as AI pricing mechanisms could effectively function as digital cartels, according to the study, which does not address whether higher profits might invite competition.

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[9] Wang, Q., Huang, Y., Singh, P. V., & Srinivasan, K. (2023). *Algorithms, artificial intelligence and simple rule-based pricing* (Working Paper). Wharton School, University of Pennsylvania.

[10] Federal Trade Commission. (2023, September 26). *FTC Sues Amazon for Illegally Maintaining Monopoly Power.*

While large retailers and travel websites have long leveraged algorithmic pricing, advancements in technology have made these tools accessible to small-scale sellers as well.[11] The benefits of algorithmic pricing are clear: it enables sellers to remain competitive by responding rapidly to market conditions. However this pricing strategy also introduces new challenges, such as unpredictable interactions between competing algorithms and even the potential for outcomes that would appear collusive.[12] Despite its growing importance, both regulators and the general public lack comprehensive knowledge about how algorithmic pricing operates in practice. This pricing mechanism not only enhances the efficiency and profitability of sellers but also introduces new market complexities. Algorithmic sellers may dominate in price competition, making it increasingly difficult for non-algorithmic sellers to sustain their businesses; algorithmic sellers experience rapid price fluctuations, sometimes changing prices tens or even hundreds of times per day, leading to potential market volatility.[13] While this level of automation benefits sellers by elevating sales volume and profits, it may also create unintended consequences such as price volatility, market manipulation, and unfair advantages.

Dynamic pricing relies heavily on artificial intelligence-based technologies. Because of this, businesses' dynamic pricing practices are sometimes governed by ethical charters designed to minimize the potential negative impacts of artificial intelligence. In a study conducted by the Capgemini Research Institute, "almost half (45 percent) of organizations [surveyed] have […] defined an ethical charter to provide guidelines on AI development"[14]. Some of the main features of these charters include recommendations regarding transparency and accountability, protection of consumers' personal data, and diversification of the content that artificial intelligence programs are trained on[15]. Because of the risk of bias in artificial intelligence programs—especially those utilized in marketing and hiring processes—companies' charters incorporate strategies for reducing bias and utilizing more expansive datasets. While many

[11] Grewal, D. (2023, November 18). Leveraging in-store technology and AI: Increasing customer and employee efficiency and enhancing their experiences. Journal of Retailing.
[12] Saveri, Joseph, and Steven Williams. Schmidig v. RealPage . 23 Jan. 2023
[13] Aparicio, Diego, et al. "The Pricing Strategies of Online Grocery Retailers." National Bureau of Economic Research, 1 Apr. 2021.
[14] Thieullent, Anne-Laure, et al. (18 February 2021). "AI and the Ethical Conundrum: How Organizations Can Build Ethically Robust AI Systems and Gain Trust." Capgemini.
[15] Deep Learning vs. Machine Learning: what's the difference? (2024, October 3). IMD Business School for Management and Leadership Courses.

companies have embraced charters, some have established "ethics-by-design methodolog[ies] … [and] integrated governance program[s]". IBM in particular has "developed a holistic AI ethics framework," which exhorts companies to consider three factors when harnessing artificial intelligence: the "economic impact" of implementing AI guidelines, the company's "reputational impact," and the company's technological capabilities. According to IBM's report, if companies develop comprehensive guidelines for artificial intelligence use, they will likely see "direct financial benefits … such as cost savings, increased revenue, or reduced cost of capital" and gain a more committed customer base[16]. Ultimately IBM's guidelines encourage companies to create "an AI Ethics Board infrastructure and staff … [to] enable the development of management system tooling that improves automated documentation and data management."[17] Deloitte takes a similar approach—in Deloitte's guidelines for the use of artificial intelligence, the company recommends that leaders "mandate trainings that outline the ethical principles of AI" and encourages leaders to "draft a plan for introducing a newly enhanced product into the market and assign accountability for product implementation and ownership."[18] Companies also typically have specialists ready to address any biases or risks that arise in their AI programs. Some have even prioritized incorporating more stringent guidelines into the development of artificial intelligence programs instead of simply establishing guidelines for the use of such programs. In one instance, "Spanish banking giant CaixaBank … adapted its existing privacy methodology and validation processes for the development of AI models."[19] Ultimately, many companies have centered their policies around their customers, focusing on the public perception of artificial intelligence use and embracing AI guidelines that prioritize data protection.

Government Responses to Artificial Intelligence

A number of regulatory concerns arise when firms engage in AI-driven dynamic pricing. First, exploiting willingness to pay becomes problematic if a firm charges higher prices to those who are willing (or able) to pay more, as consumers in the

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[16] Assessing ROI of AI ethics and governance initiatives. (2024). IBM.
[17] Berente, N., et al. (2024). Why invest in AI ethics and governance? Five real-world origin stories. IBM.
[18] Shin, M. (2023, December 20). Do companies have ethical guidelines for AI use? 56% of professionals are unsure, survey says. ZDNET.
[19] Wade, M., & Yokoi, T. (2024, May 10). How to Implement AI — Responsibly. Harvard Business Review.

marketplace, if notified about the price hike, could view it as unfair.[20] On the other hand, some corporations offer discounts to specific demographics, such as students or seniors, highlighting the dual nature of pricing strategies—while some practices may appear exploitative, others are designed to provide tangible benefits to certain groups. Data privacy presents another concern, as collecting and analyzing personal information to set individualized prices can fall under data protection regimes, though data privacy is an issue regardless of whether or not pricing dynamics are implemented.

Consumer protection becomes critical when considering the use of sensitive personal data. If the algorithm relies on factors like race, gender, or health data—explicitly or even indirectly—to determine price, it can be considered discriminatory and potentially illegal in many jurisdictions. This is especially true when hidden biases in algorithms can produce discriminatory outcomes or exploit vulnerable communities. Fair competition is another significant issue, as AI-based pricing strategies might be seen as anti-competitive or manipulative if they significantly disadvantage certain consumer segments. Additionally, transparency and accountability are emphasized by regulators, particularly regarding the need for explainability in AI systems, especially when these systems directly affect consumers' financial decisions at an extremely high level. Finally, hidden algorithmic bias presents a challenge, as AI systems can unintentionally reflect biases in training data, leading to de facto discrimination among protected classes or socioeconomic groups. This concern focuses on unintentional scenarios rather than deliberate discrimination.

The intersection of these challenges influences how different jurisdictions approach AI regulation. As a result, there is a need to identify the main legislative frameworks, ethical guidelines, and enforcement trends shaping dynamic pricing strategies worldwide. One of the world's most comprehensive data protection regulations, the EU's General Data Protection Regulation (GDPR) (2016/679) governs how the personal data of EU citizens — regardless of geography —is processed and used. Although it does not explicitly address dynamic pricing, its provisions on lawful basis for processing (Article 6) and rights of data subjects (Articles 12–23) apply to any AI-driven system that uses personal data of EU citizens. Companies must either obtain

[20] Floridi, L., & Taddeo, M. (2016). What is data ethics? *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences.*

informed consent or demonstrate a legitimate interest in processing personal data for pricing strategies. Under GDPR, users have the right to understand how their data is being used. While the law does not force a detailed explanation of algorithms (the "right to explanation" remains partially debated), companies risk public backlash and possible legal scrutiny if the use of AI for price discrimination is hidden.[21] Since the 1990s, amid intensifying competition with the United States for technological dominance, the European Union has emerged as the world's principal technological regulator, demonstrating how a major jurisdiction can effectively impose its regulatory standards globally. By setting a stringent benchmark for data protection and algorithmic transparency, the regulation not only influences how companies implement AI-driven pricing strategies within the EU but also encourages similar regulatory approaches in other jurisdictions worldwide. Moreover, the Unfair Commercial Practices Directive (UCPD) (Directive 2005/29/EC) prohibits misleading or aggressive commercial practices. If an e-commerce platform uses AI in a way that can be understood as misleading consumers about the nature of pricing—whether through hidden surcharges or non-transparent individualized pricing—regulators could interpret it as an unfair commercial practice. A level of enhanced opacity makes it harder for consumers to discern the true cost they will pay, as algorithmic manipulation effectively masks additional fees. According to Hacker (2021), the UCPD has been increasingly cited in legal scholarship as a potential tool for addressing hidden algorithmic manipulations in the consumer context.[22]

The European Commission's AI Act, now law as of 2024, categorizes AI systems using a risk-based framework. Under the Act, dynamic pricing applications in e-commerce generally fall into the minimal-risk category, meaning they are not subject to the strict controls reserved for high-risk systems. However, if dynamic pricing algorithms are employed in contexts that significantly affect individual rights—such as in credit scoring or consumer-facing sectors where personalized pricing could lead to unjustified discrimination—they might be reclassified as high-risk. As Veale and Zuiderveen Borgesius (2021) note, if these systems cross certain thresholds—by, for example, systematically discriminating against protected groups or infringing on

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[21] General Data Protection Regulation. (2016). *Regulation (EU) 2016/679 of the European Parliament and of the Council*.

[22] Hacker, P. (2021). *Manipulation by algorithms: Exploring the triangle of unfair commercial practice, data protection, and privacy law*. European Law Journal.

socio-economic rights—they could come under closer regulatory scrutiny, necessitating more rigorous transparency, oversight, and accountability measures. Given the evolving nature of AI governance, companies should closely monitor developments, as practices currently considered minimal risk might face tighter regulation in the future if significant consumer harm is demonstrated.[23]

Reaching beyond the scope of individual companies' charters or countries as a whole, the UNESCO "Recommendation on the Ethics of Artificial Intelligence" provides a comprehensive set of guidelines for governments utilizing artificial intelligence for any purpose. The "Recommendation" advises governments and companies to ensure that "no human being or human community should be harmed or subordinated, whether physically, economically, socially, politically, culturally or mentally during any phase of the life cycle of AI systems". Ultimately, UNESCO's recommendations for the use of artificial intelligence center around the potential for artificial intelligence to infringe upon human rights, commanding individuals working with artificial intelligence technology to "comply with applicable international law and domestic legislation, standards and practices"[24]. Using legal boundaries as an ethical standard, UNESCO's guidelines highlight the importance of human dignity in the field of artificial intelligence.

In the United States, no single comprehensive federal law governs AI-based dynamic pricing. Instead, regulation typically falls under the Federal Trade Commission (FTC) mandates to undertake unfair, deceptive, or anticompetitive practices. Historically, the FTC has acted against price-fixing and deceptive advertising, though not specifically on AI-driven price discrimination, since the technology has just arisen in recent history. The FTC has released guidance on the use of AI in business contexts, emphasizing that companies must avoid discriminatory or deceptive practices even when using automated tools (FTC, 2020). If AI-driven pricing leads to unfair discrimination or consumer deception, the FTC could invoke Section 5 of the FTC Act, prohibiting "unfair or deceptive acts or practices in or affecting commerce." Recent

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[23] Veale, M., & Zuiderveen Borgesius, F. J. (2021). *Demystifying the draft EU Artificial Intelligence Act: Analysing the good, the bad and the unclear elements of the proposed approach. Computer Law Review International.*

[24] Recommendation on the ethics of artificial intelligence. (2021). UNESCO.

developments show the FTC has significantly ramped up its enforcement efforts against AI-driven pricing and surveillance-based price discrimination. The agency recently issued orders to eight intermediary companies to investigate their use of AI-based pricing algorithms, consumer data collection, and competitor data tracking. The FTC and the U.S. Department of Justice (DOJ) launched a joint strike force aimed at eliminating anti-competitive, deceptive, or fraudulent business practices linked to AI-powered pricing models.

Although there has been no federal mandate on the use of AI in the United States, legal guidelines and government recommendations have attempted to limit the power of artificial intelligence. Under the Biden administration, the White House issued an "AI Bill of Rights," which stated "that algorithms should not be discriminatory and systems should be used as designed in an equitable way; and that citizens should have agency over their data and should be protected from abusive data practices through built-in safeguards." Additionally, the AI Bill of Rights sought to allow individuals "to opt out of AI systems in favor of a human alternative." The AI Bill of Rights followed the trend of "human-centric" artificial intelligence regulations, prioritizing individuals' right to digital privacy and advocating for more "comprehensive" strategies for combating the risks of AI[25]. In a similar vein, the Algorithmic Accountability Act of 2022 sought to enshrine artificial intelligence regulations in law; though it ultimately did not pass, it still provides a conceptual foundation for some lawmakers. The act would require "companies to conduct impact assessments for bias, effectiveness and other factors, when using automated decision systems to make critical decisions" and "clarif[ies] what types of algorithms and companies are covered" in order to effectively regulate artificial intelligence[26]. According to the law firm White & Case, "there are more than 120 AI bills being considered by the US Congress, covering a wide range of issues such as AI education, copyright disclosure, AI robocalls, biological risks, and AI's role in national security."[27] Current frameworks for AI use seek to regulate AI in all of its forms, rather than only focusing on AI use in a specific field.

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[25] Heikkilä, M. (2022, October 4). The White House just unveiled a new AI Bill of Rights. MIT Technology Review.

[26] Chu, K. (2022, February 3). Wyden, Booker and Clarke Introduce Algorithmic Accountability Act of 2022 To Require New Transparency And Accountability For Automated Decision Systems. U.S. Senator Ron Wyden of Oregon.

[27] AI Watch: Global regulatory tracker - United States. (2024, May 13). White & Case LLP.

With the return of Donald Trump to the U.S. presidency, artificial intelligence regulation is expected to become less stringent; during President Trump's first term, the Office of Budget and Management released a memo stating that "federal agencies must avoid regulatory or non-regulatory actions that needlessly hamper AI innovation and growth[28]. Shortly after his reelection, President Trump released an executive order entitled *Removing Barriers to American Leadership in Artificial Intelligence*[29], reaffirming a shift from the regulatory posture of the Biden administration, emphasizing deregulation and free-market innovation over stringent oversight. Trump's directive revokes prior AI policies, including Biden's Executive Order 14110, which focused on safety, security, and ethical considerations in AI development, eliminating what it perceives as barriers to innovation, and asserting that such regulations hinder the United States' ability to maintain global leadership in AI. While Biden's policy emphasized establishing standards to mitigate risks such as bias and discrimination, Trump's order prioritizes rapid innovation and economic growth, potentially at the expense of what the previous administration might have considered as comprehensive ethical safeguards.

Some states have begun introducing their own AI and data privacy regulations that could affect dynamic pricing. The California Consumer Privacy Act (CCPA) and California Privacy Rights Act (CPRA) impose data access rights and transparency requirements; the CPRA might force companies to disclose whether personal data influences pricing. Additionally, bills like the Algorithmic Accountability Act (first introduced in 2019 at the federal level, though not enacted) could set precedents for requiring more extensive audits and disclosures around how AI systems, including dynamic pricing engines, impact consumers.[3031] Certain industries—like insurance or credit—face strict legal constraints on price discrimination. For example, state insurance commissions regulate how insurers can set premiums. While not directly parallel to e-commerce, restrictions across separate industries hint at growing legislative attention to algorithmic fairness in pricing decisions, especially moving forward in the digital golden age.

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[28] Kumayama, K., Levi, S., & Ridgway, W. (2025, January 14). US Federal Regulation of AI Is Likely To Be Lighter, but States May Fill the Void. Skadden, Arps, Slate, Meagher & Flom LLP.

[29] Trump, D. J. (2025, January 23). *Removing barriers to American leadership in artificial intelligence* (Executive Order 14179). The White House.

[30] California Civil Code § 1798.100–1798.199.100 (2018), *California Consumer Privacy Act of 2018*

[31] Clarke, Y. D. (2019). *Algorithmic Accountability Act of 2019*, H.R. 2231, 116th Cong

Beyond the established concerns about price discrimination and lack of transparency in AI-driven pricing, there are several new dimensions of risk associated with algorithmic pricing models that regulators and policymakers could address, most of which are not very well known, allowing for a more nuanced understanding of AI's impact on competition, consumer welfare, and economic fairness[32]. One of the most difficult challenges for regulators is the shift from explicit collusion (traditional price-fixing agreements) to tacit collusion, where AI pricing algorithms autonomously learn to coordinate pricing without direct communication between firms. The authors argue that pricing algorithms, particularly RL-based models, can systematically adjust prices in response to competitors, leading to prices being higher than they might otherwise be without explicit coordination, perhaps raising legal questions. They further assert that price coordination may emerge when multiple firms rely on a common third-party AI pricing system, holding that such systems act as de facto hubs that synchronize pricing across multiple companies. There is an argument that traditional antitrust frameworks struggle to regulate this phenomenon as the firms do not explicitly agree to collude, but the third party is explicit and could be seen as violating existing laws. Beyond the third-party issue, unlike traditional price-fixing schemes, often involving detectable agreements between firms, AI-driven tacit collusion would not involve intent to collude. The authors note that regulators typically rely on evidence of explicit agreements, which would not exist with algorithmic tacit collusion. The authors also express concern regarding what they term "willpower fatigue"—a momentary phenomenon when customers are willing to pay higher prices than at other times. AI might be able to detect such moments (e.g., late at night or after multiple search attempts) and price accordingly. This practice might raise ethical and legal concerns, but it might also be true that AI tools lead multiple firms to compete for these moments, thus bringing competition to bear because the AI detected greater customer willingness to pay.[33]

A comprehensive review by the Australian Competition and Consumer Commission (ACCC) unravels the new risks and advantages of algorithmic pricing in online marketplaces. While pricing algorithms create efficiencies, reducing costs for

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[32] Cantatore, F., & Marshall, B. (2021). Safeguarding consumer rights in a technology driven marketplace. *Adelaide Law Review.*

[33] Cantatore, F., & Marshall, B. (2021). Safeguarding consumer rights in a technology driven marketplace. *Adelaide Law Review.*

sellers and increasing competition, they also introduce several potential harms to consumers and fair market dynamics. The ACCC report underscores that algorithmic pricing can inadvertently lead to collusion, where competitors adjust their prices not through direct communication but by relying on the same algorithmic pricing models. Similar to tacit collusion, this can stabilize higher-than-competitive price levels but with AI-driven real-time adjustments. Nevertheless, the ACCC warns that these pricing patterns could fall under anti-competitive behavior under Australian law. Dynamic pricing algorithms are designed to maximize profit by responding to real-time supply and demand changes. However, in crisis situations (such as the COVID-19 pandemic), the ACCC found that automated price adjustments led to extreme price spikes for essential goods like hand sanitizers and face masks[34]. The ability of AI-driven pricing to exploit market scarcity highlights consumer protection gaps that traditional regulatory tools may not fully address. The ACCC suggests that large online platforms, such as Amazon and eBay, bear responsibility for monitoring and mitigating AI-driven price manipulation. Some companies have introduced internal policies to prevent excessive price hikes, but these self-regulatory measures remain inconsistent and largely discretionary. The ACCC argues that stronger governmental oversight may be needed to curb exploitative pricing behavior in digital marketplaces.[35]

Case Study

Growing interest in algorithmic pricing underscores its growing role in e-commerce, particularly as online marketplaces enable real-time price adjustments based on competitor behavior and market conditions[36]. Amazon Marketplace provides a useful setting for studying algorithmic pricing due to its scale, the coexistence of automated and manual pricing strategies, and the long-standing use of dynamic pricing by both Amazon and third-party sellers. Sellers on the platform are able to adjust their pricing strategies to enhance visibility and sales, particularly in relation to the Buy Box feature, which determines the promoted seller for a given product. Because sellers

[34] It is possible that, absent the price changes, shortages would have been more exaggerated, leading to a first-come-first-served sorting mechanism, as opposed to a pricing mechanism, that benefited people with greater time and other resources for searching online.
[35] Australian Competition and Consumer Commission. (2022). *Digital platform services inquiry: Interim report no. 4 – General online retail marketplaces*.
[36] Gupta, S. (2023, August 19). Identification of benefits, challenges, and pathways in E-commerce industries: An integrated two-phase decision-making model. Sustainable Operations and Computers.

actively seek to achieve the Buy Box, and approximately 82% of Amazon sales occur through the Buy Box, it seems reasonable to conclude that pricing algorithms play a key role in shaping competition on the platform.[37] Algorithmic pricing influences sellers' ability to compete for this visibility, as pricing dynamics, among other factors, affect Buy Box eligibility.

To address this gap, Chen et al. developed a methodology for attempting to break down the patterns of the algorithmic pricing model on Amazon Marketplace; more specifically to analyze the platform's reliance on it. Conducted by Le Chen, Alan Mislove, and Christo Wilson, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace* offers an examination of how automated pricing tools influence market dynamics, seller performance, and consumer experiences on Amazon's platform.[38] The study examined algorithmic pricing on Amazon Marketplace by examining decisions made by merchants selling any of 1,641 best-seller products in 2014 and 2015. It identified algorithmic pricing strategies used by over 500 sellers, examined the characteristics of these sellers, and assessed how these strategies influence marketplace dynamics. The study employed a novel approach to detecting algorithmic pricing by analyzing price fluctuations as time-series data, identifying sellers whose prices consistently tracked target prices, such as the lowest advertised price or Amazon's own price, suggesting the use of algorithmic tools. The authors concluded that algorithmic sellers tend to be more successful than non-algorithmic sellers in e-commerce, regardless of product or price categories. Despite offering fewer products than other sellers, these sellers receive significantly more customer feedback, indicating higher sales volumes. Moreover, algorithmic sellers win the Buy Box more frequently, even when they do not always offer the lowest price. This suggests that other factors, such as customer ratings and fulfillment methods, influence the Buy Box selection process.

However, Chen et al. also noted some drawbacks associated with algorithmic pricing. Frequent price fluctuations in e-commerce can contribute to consumer frustration, particularly if buyers perceive dynamic pricing as unfair or manipulative. However, studies examining consumer reactions to algorithmic pricing remain limited,

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[37] Team, B. (2024, September 10). How to win the buy box on Amazon: Eligibility + strategies.

[38] Chen, L., Mislove, A., Wilson, & Christo Wilson, B. (2016, April 11). An empirical analysis of algorithmic pricing on Amazon Marketplace: Proceedings of the 25th International Conference on World Wide Web. ACM Other conferences.

and perceptions may vary across platforms and contexts.[39] In some cases, algorithmic interactions have resulted in extreme price distortions, with one widely cited example involving competing repricing algorithms driving the price of a used textbook to $24 million. While such instances illustrate potential unintended consequences of automated pricing, they do not necessarily imply unpredictability, as algorithms adjust prices based on predefined rules and inputs.

Their concerns about algorithmic pricing also extend to the potential for collusion. While price-fixing is illegal, there have been documented instances in which sellers were prosecuted for implementing a price-fixing scheme on Amazon Marketplace using automated tools.[40] Importantly, the issue in that case was not the use of algorithms alone but the underlying agreement among sellers to coordinate prices, which violated antitrust laws.

To gain further insight into the factors influencing Amazon's pricing ecosystem, Chen et al. also investigated the Buy Box algorithm using machine learning techniques. Their findings indicate that, among observable variables, price is the most important factor in determining Buy Box selection[41], but customer-centric metrics such as seller feedback and ratings also play a crucial role. These findings provide empirical evidence that sellers adopting algorithmic pricing strategies have a competitive edge, not just in terms of adjusting prices but also in securing a stronger marketplace presence through the Buy Box. The calculation of prices on Amazon's New Offers page includes both the base price and the total price, which factors in the lowest-cost shipping option. Throughout this analysis, references to price denote the total price, as Amazon utilizes this metric when users sort products by price, preventing them from sorting based solely on base price[42]. This dataset has two key limitations. It is inherently biased

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[39] Dublino, J. (n.d.). Dynamic pricing: What is it & how it effects e-commerce. business.com.

[40] "Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division's First Online Marketplace Prosecution." Justice.gov, US Department of Justice, 6 Apr. 2015

[41] Selection by Amazon as to who receives the Buy Box.

[42] Since third-party sellers and Amazon itself can adjust their prices at any time, determining an optimal crawling frequency is crucial. To assess this, a high-resolution dataset was created, selecting five best-selling products and crawling their product pages and the first two seller pages, covering up to 20 sellers, every minute over three days. Chen et al. revealed that price updates are highly dynamic, with 40% of changes occurring within a minute of the previous update. However, some rapid fluctuations, where old prices briefly reappear, are attributed to Amazon's distributed infrastructure rather than actual seller price changes. These inconsistencies, caused by Amazon's system taking up to 15 minutes to synchronize, informed the decision to crawl every 25 minutes, a balance between covering more products

toward best-selling products. A comparison with a random sample of 2,158 Amazon products revealed that best-sellers tend to have more competing sellers and lower prices than randomly selected items. Second, the data was collected using browsers not logged into Prime accounts, meaning the dataset reflects the majority of Amazon users but may not fully capture variations experienced by Prime members. Since Amazon modifies listings for Prime users, particularly highlighting Prime-eligible sellers and expedited shipping options, some conclusions may not apply to them.[43] The Buy Box itself is highly dynamic, with 50% of products experiencing more than 14 price changes over six weeks, and some undergoing hundreds of changes. However, the seller occupying the Buy Box remains more stable, with 31% of products maintaining the same Buy Box winner throughout the observation period.

An investigation into the Buy Box algorithm showed that the highest-ranked seller on the New Offers page does not always win the Buy Box. Only 60% of the top-ranked sellers secured it, and lower-ranked sellers occasionally won, reinforcing that factors beyond price contribute to selection. To better understand these factors, a machine learning model was developed to predict the Buy Box winner based on seven features: price difference relative to the lowest price, price ratio relative to the lowest price, average rating, positive feedback percentage, total feedback count, whether the seller used Fulfilled by Amazon, and whether the seller was Amazon itself. A Random Forest classifier was used, achieving 75–85% accuracy in predicting Buy Box winners, significantly outperforming naïve baselines that relied solely on lowest price or rank. Surprisingly, using *Fulfilled by Amazon* (FBA) had minimal importance, contradicting the common belief that it strongly impacts Buy Box selection. While Amazon had a slight

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and maintaining an efficient frequency.# This technical limitation of Amazon's pricing system is important to note when considering sources of consumer dissatisfaction and confusion. Two separate crawls were conducted. The first crawl, from September 15, 2014, to December 8, 2014, included 837 best-selling products with at least two sellers. It focused on seller pages but did not include product pages containing the Buy Box. The second crawl, conducted between August 11, 2015, and September 21, 2015, expanded to 1,000 best-selling products, capturing both product pages, including the Buy Box, and the first two pages of third-party sellers. Since 96% of sellers who frequently changed prices appeared within the first two pages, limiting data collection to these pages significantly reduced the volume of data while still capturing meaningful pricing behaviors. Notably, these two crawls covered different products, with only 196 products in common, reflecting the evolving nature of best-seller rankings. Despite this, the pricing and seller characteristics remained consistent across both datasets.

[43] Dhandapani, S. (2025, January 31). Advantages of becoming an Amazon prime seller - analytics tools for Amazon and Walmart sellers. Analytics Tools for Amazon and Walmart Sellers - Your Virtual Assistant for Amazon and Walmart Business!

advantage in securing the Buy Box, this could be attributed to unmeasured features like sales volume and customer service metrics rather than direct favoritism in the algorithm.

Overall, this analysis provides insight into the complex and dynamic nature of Amazon's pricing and Buy Box algorithm. The findings suggest that while price is a key factor in seller rankings and Buy Box selection, additional attributes such as seller reputation and performance significantly influence outcomes. Furthermore, the detection of algorithmic pricing highlights how sellers increasingly rely on automated strategies to stay competitive, making pricing dynamics more volatile.[44] These findings are crucial for both sellers and consumers, shedding light on how pricing strategies evolve in response to Amazon's marketplace algorithms.

Final Thoughts

The emergence of AI-driven dynamic pricing represents a significant evolution in market dynamics, offering unprecedented opportunities for businesses to optimize revenue while simultaneously presenting complex regulatory challenges. As demonstrated through empirical analysis of platforms like Amazon Marketplace, algorithmic pricing affords sellers measurable advantages in visibility and sales volume, though not without potential consequences for market competition and consumer welfare. The regulatory landscape remains fragmented and evolving, with jurisdictions like the European Union adopting comprehensive frameworks while the United States pursues a more decentralized approach that may be shifting toward deregulation under the current administration. This tension between innovation and regulation reflects broader societal questions about the proper boundaries of algorithmic decision-making in commerce. The empirical evidence suggests that while AI-powered pricing systems deliver substantial efficiency gains, they also introduce novel forms of market behavior that traditional antitrust frameworks struggle to address—particularly regarding tacit collusion and third-party algorithmic intermediaries. Moving forward, policymakers and businesses alike must navigate this complex terrain, balancing the imperative for technological advancement against the need to preserve fair competition, protect

[44] Nunan, D. (2022, June 22). Value creation in an algorithmic world: Towards an ethics of dynamic pricing. Journal of Business Research.

consumer interests, and maintain transparent market mechanisms in an increasingly algorithmic economy.

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