Algorithmic Pricing: Implications for Marketing Strategy and Regulation

Martin Spann, Marco Bertini, Oded Koenigsberg, Robert Zeithammer, Diego Aparicio, Yuxin Chen, Fabrizio Fantini, Ginger Zhe Jin, Vicki Morwitz, Peter Popkowski Leszczyc, Maria Ana Vitorino, Gizem Yalcin Williams, Hyesung Yoo

January 6, 2025

Contact:

Martin Spann (LMU Munich, spann@lmu.de) – corresponding
Marco Bertini (Esade, Universitat Ramon Llull, marco.bertini@esade.edu)
Oded Koenigsberg (LBS, okoenigsberg@london.edu)
Robert Zeithammer (UCLA, robert.zeithammer@anderson.ucla.edu)
Diego Aparicio (IESE, daparicio@iese.edu)
Yuxin Chen (NYU Shanghai, yc18@nyu.edu)
Fabrizio Fantini (Evo Pricing, fab@evopricing.com)
Ginger Zhe Jin (University of Maryland, jin@econ.umd.edu)
Vicki Morwitz (Columbia University, vgm2113@columbia.edu)
Peter Popkowski Leszczyc (University of Queensland, p.popkowski@business.uq.edu.au)
Maria Ana Vitorino (INSEAD, maria-ana.vitorino@insead.edu)
Gizem Yalcin Williams (UT Austin, gizem.yalcin@mccombs.utexas.edu)
Hyesung Yoo (University of Toronto, hyesung.yoo@rotman.utoronto.ca)

Acknowledgement:

The authors thank the organizers of the 12th Invitational Choice Symposium at INSEAD.

Algorithmic Pricing: Implications for Marketing Strategy and Regulation

Abstract

Over the past decade, a growing number of firms have delegated pricing decisions to algorithms in consumer and business markets such as travel, entertainment, and retail, as well as in platform markets such as ride-sharing. In this paper, we define algorithmic pricing as "the use of programs to automate the setting of prices". Firms adopt algorithmic pricing to optimize their prices in response to changing market conditions and to take advantage of the efficiency gains from automation. Advances in information technology and the increased availability of digital data have further facilitated the use of algorithm-driven pricing strategies. However, the adoption of algorithmic pricing is a strategic decision that must align with a company's existing and future marketing strategies. In addition, algorithmic pricing is likely to encounter various regulatory concerns regarding the use of customer data, the legality of price discrimination, and potential threats to competition. The aim of this paper is to discuss the implementation of algorithmic pricing in the context of firms' marketing strategies and regulatory frameworks, while outlining an agenda for future research in this increasingly important area.

Keywords: programmatic pricing, dynamic pricing, personalized pricing, managerial decision-making, marketing strategy, regulatory concerns

1. Introduction

Over the past decade, a growing number of firms have delegated pricing decisions to algorithms in consumer and business markets such as travel, entertainment, and retail, as well as in platform markets such as home or ride sharing. In this paper, we define algorithmic pricing as "the use of programs to automate the setting of prices". Although airlines have been using yield management systems for decades (Elmaghraby & Keskinocak, 2003), and time-varying or individualized discounts have been widely used since the introduction of scanners and loyalty programs in retail stores (Gabel & Guhl, 2022), the last decade has seen an increase in the use of algorithmic pricing.

For example, Airbnb rolled out an algorithmic tool to help hosts set prices in 2013 (Hill, 2015). L. Chen, Mislove, and Wilson (2016) found that one-third of Amazon sellers of best-selling products likely used algorithmic pricing, although the specific algorithm they used remains unclear. Cohen, Hahn, Hall, Levitt, and Metcalfe (2016) showed that surge pricing on the UberX service – set by the platform's algorithm – helped match ridesharing demand and supply in real time, resulting in an overall gain in consumer surplus of $6.8 billion in the U.S. in 2015 alone.

More recently, Brown and MacKay (2023) tracked high-frequency price data for OTC allergy medications at the five largest online retailers and found that while these retailers updated prices at regular intervals, the intervals varied widely across firms, suggesting the use of algorithmic pricing. Calder-Wang and Kim (2023) collected data on when property management companies adopted rent-optimization software. They found that at least 25 percent of buildings, or 34 percent of units in their data, were using algorithmic pricing as of 2019. As with ride-sharing, they found that algorithmic pricing allowed building managers to set prices that were more responsive to macro conditions, such as booms and busts, than non-adopters in the same market.

Firms using algorithmic pricing seek to optimize their prices in response to changing market conditions and to leverage efficiency gains from automation (Bertini & Koenigsberg, 2021). The greater availability of digital data and developments in information technology have facilitated the use of algorithms in pricing.

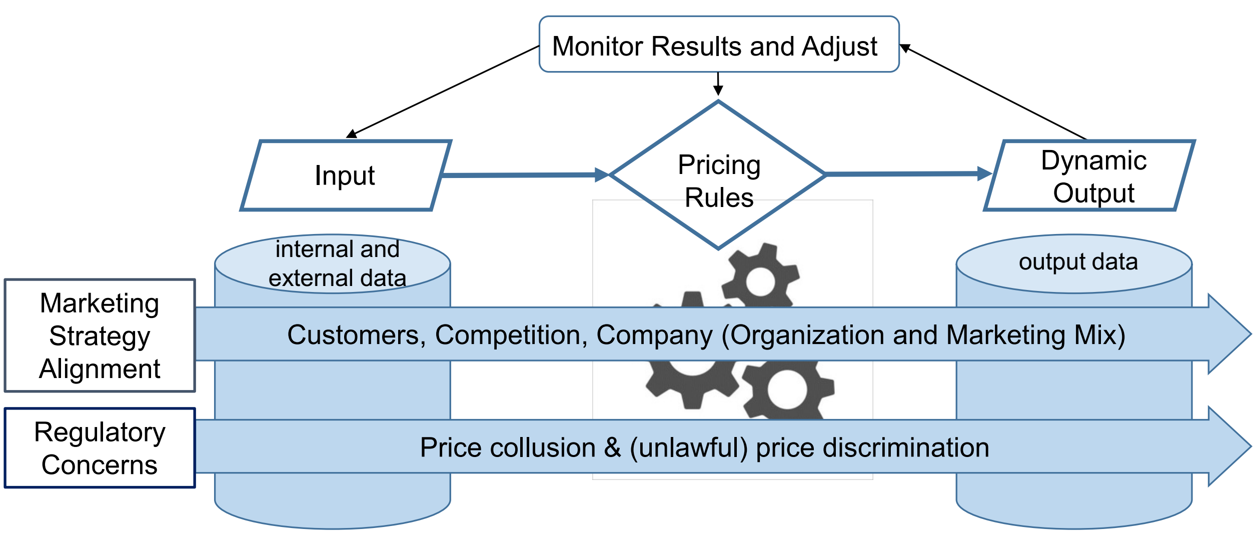
However, the adoption of algorithmic pricing is a strategic decision that must align with a company's existing and future marketing strategies. In addition, companies using algorithmic pricing must carefully consider the regulatory landscape. Antitrust concerns and consumer protection issues may arise, particularly regarding collusion, (unlawful) price discrimination, and data privacy. To ensure compliance, firms may need to adjust their strategies and algorithms to avoid violating competition and consumer protection laws.

Despite the widespread adoption of algorithmic pricing, a comprehensive analysis of its implementation considerations within firms' business strategies and regulatory frameworks is lacking. Furthermore, there is no consistent and simple definition of algorithmic pricing. Several review articles focus on different aspects of algorithmic pricing or related concepts. Seele, Dierksmeier, Hofstetter, and Schultz (2019) explore ethical considerations and distinguish dynamic and personalized pricing as subcategories of algorithmic pricing. Calvano, Calzolari, Denicolò, and Pastorello (2019) discuss competition-related issues of algorithmic pricing. Kopalle, Pauwels, Akella, and Gangwar (2023) study dynamic pricing with a focus on the retail industry and discuss the main drivers of dynamic price changes. However, previous research has not examined the managerial challenges of implementing algorithmic pricing.

This paper aims to address these gaps by examining the implementation of algorithmic pricing in the context of firms' marketing strategies and regulatory frameworks, while outlining an agenda for future research in this important area. In addition, we define and compare algorithmic pricing to other forms of pricing. We contribute to the literature by examining the strategic alignment of algorithmic pricing with respect to customers, competition, and the firm, i.e., its organization and marketing mix, and the consideration of key regulatory concerns. In addition, we provide empirical support for the views we offer on this alignment based on interviews with pricing executives, a survey of pricing managers, and a case study. Our discussion highlights the many interdependencies between the implementation of algorithmic pricing, a firm's marketing strategy, and regulatory frameworks. For example, we show that firms' strategic considerations and market forces mitigate many regulatory concerns —fear of customer backlash discourages the adoption of unfair algorithmic pricing practices, while managers anticipate increased price competition rather than collusive behavior.

To guide our discussion of the strategic integration of algorithmic pricing, we structure its implementation according to the components of an algorithmic process, i.e., the data input, the rules that transform that input, and the output (see Figure 1). This provides a framework for analyzing the key factors involved in implementing this pricing strategy, focusing on alignment with marketing strategies and addressing regulatory concerns that firms must consider.

Figure 1: Algorithmic Pricing Implementation



The remainder of the paper is organized as follows. In Section 2, we define algorithmic pricing, compare it to other forms of pricing, and outline our framework for analyzing implementation (Figure 1). In Section 3, we discuss the implementation of algorithmic pricing in terms of marketing strategy alignment and in Section 4 in terms of regulatory concerns. Section 5 concludes the paper with a discussion of research priorities in this area.

2. Algorithmic Pricing: Definition, Comparison, and Analysis Framework

2.1. Definition and Comparison to Other Forms of Pricing

We generally define algorithmic pricing as "*the use of programs to automate the setting of prices.*"[1] In algorithmic pricing systems, input data is transformed into output based on the rules of the algorithm with the goal of automatically setting prices (see Table 1). Input data refers to the selection of variables to include in pricing, such as weather, consumer behavior, competitor prices, and historical data (Seele et al., 2019). Rules determine how prices, which may vary across time, consumers, and products, are set based on a particular combination of input data. Output refers to the prices determined by the algorithm.

Table 1: Components of algorithmic process to set prices

Component	***Examples***
Input data	Historical consumer behavior, product attributes, competitor prices, weather, inventory levels
Pricing rules	Price-sensitivity to changes in demand, supply, competitor prices
Output	Price(s) across time, consumers, and products

Table 2 compares algorithmic pricing to dynamic pricing, participative pricing and traditional pricing methods. The algorithm can change prices across time, consumers and products,

[1] Our definition of algorithmic pricing does not include algorithms that may indirectly influence pricing, such as those used by donation-based live streaming platforms (e.g., S. Lu, Yao, Chen, and Grewal (2021)).

resulting in dynamic and/or personalized pricing (Seele et al., 2019). Therefore, *dynamic pricing*[2] is the result of using *algorithmic pricing*, because it requires algorithms to adjust prices based on real-time market conditions.[3] Algorithmic pricing also differs from participative pricing, in which both dynamic price changes and personalized prices can be the result of direct customer interaction in a participative pricing mechanism such as an auction or negotiation (Spann et al., 2018).

The key difference between algorithmic pricing and traditional pricing methods is automation. While traditional methods involve manual price setting by managers, algorithmic pricing uses algorithms to set prices based on predefined rules and data analysis. Prices based on algorithmic pricing systems are typically neither predetermined nor pre-announced as in traditional pricing.

Table 2: Differences between algorithmic pricing and other forms of pricing

Criteria	***Algorithmic pricing***	***Dynamic pricing***	***Participative pricing***	***Traditional pricing***
Pricing automation	Yes	Yes	No	No
Temporal dynamics	Yes	Yes	No	No
Personalized pricing	Yes	No	Yes	Possible
Direct customer interaction in pricing	No	No	Yes	No

2.2. Framework to Analyze the Implementation of Algorithmic Pricing

Figure 1 above illustrates our framework for analyzing the strategic and implementation aspects of algorithmic pricing. The horizontal process follows the logic of algorithms, using input data that is transformed into output based on the algorithm's rules. As outlined above, input data

[2] Dynamic pricing is defined as (automated) price changes that are triggered by changes in market demand drivers (Kopalle et al. (2023)). Therefore, pre-announced price differences over time that do not change dynamically, such as happy hour offers every day between 6 p.m. and 8 p.m. in a bar, are not considered dynamic pricing.

[3] Algorithmic pricing is a broader concept that includes dynamic pricing as well as personalized pricing and non-dynamic algorithmic pricing, such as volume-based pricing in business-to-business (B2B) transactions. Algorithmic pricing can be dynamic and it can be personalized, but it does not have to be both at the same time (OECD (2018)).

refers to the selection of variables to include in pricing and rules determine how prices are set based on a particular combination of input data. Output-related decisions include how these algorithmically determined prices are implemented and communicated, for example, through different channels. In addition, the firm needs to monitor each step of the algorithmic process and adjust as necessary.

These decisions along the algorithmic process must be consistent with the firm's marketing strategy and external (regulatory) concerns. Next, we describe the components of marketing strategy according to customers, competition, company (organization and marketing mix), and outline potential regulatory concerns regarding price collusion and (unlawful) price discrimination that firms must consider when implementing algorithmic pricing. In the following sections, we discuss each of these aspects. While our focus is on business models that directly sell products or services to individual consumers (B2C), many ideas also apply to business-to-business (B2B) models.

2.3. Empirical Support

To provide empirical support for our discussion of algorithmic pricing, we include results from in-depth interviews with pricing executives, a survey of pricing managers, and a case study (see Table 3). Below, we outline the methodology of each study and then incorporate the results into our discussion. Additional results and details can be found in the online supplement.

Table 3: Empirical Support Used in this Paper

Type of study	***Description***
In-depth interviews	Five pricing executives
Management survey	Eighty-three pricing managers
Case study	Electronic shelf labels (ESLs) price automation in 225 offline stores

2.3.1. Interviews of Pricing Executives

We conducted five in-depth interviews with knowledgeable, global pricing experts who are at major consultancies or who are presidents of major industry organizations involved in pricing. The purpose of these interviews was to gain a high-level strategic perspective on the use and perceptions of algorithmic pricing from the interviewees' experiences with the client and member firms they work with. Table 4 lists our interviewees and their roles.

All interviews were conducted by the same member of the author team and followed a predetermined structure. After introducing our objective, each interviewee was presented with our structure for analyzing the key aspects of algorithmic pricing implementation, as shown in Figure 1. The interviews followed this structure, with follow-up questions about the issues highlighted by the interviewee. Each interview lasted approximately 30 minutes, was recorded and transcribed. We report quotes from these interviews in Sections 3.1, 3.2, 3.3, and 5 to illustrate key points.

Table 4: List of Pricing Excecutives Interviewed

Name	***Position***
Mark Billige	Chief Executive Officer, Simon-Kucher & Partners
Kevin Bright	Former Head of Pricing, Europe, McKinsey & Company
Jean-Manuel Izaret	Managing Director & Senior Partner; Global Leader, Marketing, Sales & Pricing Practice, BCG
Kevin Mitchell	President, Professional Pricing Society
Pol Vanaerde	Founder and Chair, European Pricing Platform

2.3.2. Management Survey

We conducted a survey of pricing managers to assess their perception and usage of pricing algorithms. The survey was distributed through the EPP Pricing Platform (www.pricingplatform.com), a non-profit platform with a membership of over 25,000 registered pricing professionals. In addition, the authors shared links to the survey on their LinkedIn accounts (see Web Appendix A for the survey questions).

Eighty-three managers participated in the survey, with 12 observations excluded[4], leaving 71 responses available for analysis. More than 80 percent (87.3%) of respondents said they were very or extremely familiar with their company's pricing strategies, and most (79.6%) of them were responsible for pricing decisions in their companies. The majority of companies sold less than 25 percent of their business through online channels (81.5%), had been in business for more than 20 years (79.6%), employed more than 1,000 people (68.5%), and sold products in Europe (68.5%) and the United States (24.1%). See Section 3.3 for the results of the survey.

2.3.3. Case Study: Price Automation via Electronic Shelf Labels in Offline Retailing

We present a case study on the effects of implementing Electronic Shelf Labels (ESLs) in offline retailing on price automation and dynamically changing prices. Evo[5] provided field data from one of its clients, which operates gift and memorabilia stores in zoos, aquariums, and museums. Prior to working with Evo, the client's stores had a corporate policy of making price changes only twice a year due to the high labor costs of printing price tags, deciding on new prices, and numerous other costly operational decisions. The managers felt this was clearly sub-optimal, as it did not allow stores to respond in a timely manner to changes in tastes, seasonal trends, cost shifts, and changes in the customer base.

To address these challenges, Evo proposed installing Electronic Shelf Labels (ESLs) to allow automatically set prices in physical stores while significantly reducing the cost of making such price changes. The data cover 225 different stores in the United States and Canada. See Sections 3.3 and 3.4.3 for the case study results.

---

[4] Ten excluded for incompleteness and two for inconsistencies in statements on their use of algorithmic pricing.

[5] Evo is a consulting company that helps clients optimize business decisions using artificial intelligence for price setting. A more detailed institutional description of the company is provided in Fantini and Das Narayandas (2023).

3. Implementation and Marketing Strategy Alignment

Algorithmic pricing must align with the firm's overall marketing strategy. This section assesses its fit with the overall business strategy in terms of customers, competition, and the company, i.e., its organization and marketing mix. Table 5 provides an overview of the key issues.

Table 5: Algorithmic Pricing Implementation and Marketing Strategy Alignnment

	Key Issues	*Implementation Aspects (including Monitoring)*
Customers	• Willingness to pay • Perceived price fairness • Discriminatory prices • Price transparency • CRM integration	• Availability of data input • Rules (e.g., limiting price increases in case of excess demand) • Rules (e.g., not setting prices based on gender) • Transparency about the input data used and the rules • Integration of inputs, alignment of rules, and outputs with the objectives of the CRM system
Competition	• Influence of competition Influence on competition • Risk of price wars	• Regarding data input • Regarding rules, but also data input and output • Rules of the pricing algorithms
Company: Organization	• Managerial perceptions of algorithmic pricing • Managerial qualifications • Platform and sellers • Organizational structures	• Clarify managers' roles • Provide training on understanding algorithmic output and how to monitor it • Rules: different goals of platform and sellers • Integration within company functions
Company: Price	• Pricing strategy alignment • Revenue model alignment • Impact on consumer price sensitivity and price search	• Align rules and data inputs • E.g., Subscription vs. pay-per-use • Rules and output (e.g., frequency of price change makes price comparison more difficult)
Company: Product	• Different product types (e.g., durable vs. consumable) • Consistency with brand image • Weight of product characteristics	• Differences in data requirements and rules, as well as anticipated consumer reactions • Output: price frequency and perceived quality • Price vs. other product characteristics
Company: Place	• Fit with distribution channel • Price consistency across channels (online vs. offline)	• Output (e.g., electronic shelf labels) • Input and rules
Company: Promotion	• Effect on price promotions • Interplay of advertising and algorithmic pricing	• Frequency, depth, framing (output) • Advertising engagement (e.g., CTR) as input data; joint advertising and price targeting

3.1. Customers

Algorithmic pricing can dynamically adjust prices based on changing market conditions and personalize prices for different customer segments or even individuals, using various inputs such as behavior, price elasticity, willingness-to-pay, and demographics. Done correctly, this can enhance customer satisfaction by offering discounts or personalized offers that deliver value, align with customer expectations, and match their willingness to pay. However, it is important to consider how consumers may react to various aspects of algorithmic pricing implementation in terms of input data, rules, and resulting prices (i.e., output). Existing research has explored the impact of algorithmic integration in consumers' lives, highlighting that algorithms can shape the way consumers think and feel about themselves, products, and companies, and how consumers ultimately behave (G. Y. Williams & Lim, 2024; Yalcin, Lim, Puntoni, & van Osselaer, 2022). At the same time, however, research specific to how people react to algorithmic pricing remains scarce.

Consumers' reactions to the adoption and implementation of algorithmic pricing are shaped by their beliefs and perceptions about the data that are used by the algorithms, the rules they assume govern price setting, the prices themselves and their dynamic nature. Additionally, customer perceptions of algorithmic pricing are affected by how transparent a firm is about whether it adopts algorithmic pricing, the information its pricing algorithm uses, and how prices are set. Transparency here can play a critical role in building consumer trust and influencing valuation, as transparency in this context could potentially be valued in a similar way to how price transparency is generally appreciated by consumers (Seim, Vitorino, & Muir, 2017).

Beyond the inputs, rules, and outputs, and the transparency surrounding them, consumers' reactions may also depend on their broader beliefs about companies that use pricing algorithms. A key consideration in the implementation of algorithmic pricing is that some consumers may believe that the use of pricing algorithms is inherently unfair (Haws & Bearden, 2006). Perceptions of price fairness can vary with the source of information, so even when observed prices are held constant, consumers' perceptions of fairness may differ if they become aware that an algorithm was involved in price setting (Campbell, 2007).

Inputs

Consumers may be aware or believe that factors such as their demographics, geographics, and past behavior (e.g., clicks, purchases, views) can be used as inputs in pricing algorithms. In such cases, their reactions are likely to be affected by the inputs they assume or know are considered by these algorithms. Duani, Barasch, and Morwitz (2024) found that while consumers generally perceive pricing algorithms to be less fair than human price setters, they view prices set by algorithms (vs. humans) as fairer when price discrimination is based on demographics. This is because, in the case of demographic price discrimination, consumers feel less judged by algorithms (vs. humans), and perceive algorithms' decisions as less exploitative and more justified. However, adding nuance to this discussion, previous research has also shown that consumers from certain marginalized groups may be concerned that if data identifying their group is used as an input, they will receive biased or discriminatory outcomes from algorithms, prompting them to avoid companies that use such algorithms (Barocas & Selbst, 2016).

While past research has shown that consumers are sometimes willing to provide personal information in exchange for discounts or better service, and are more willing to share data with algorithms than human agents (Lucas, Gratch, King, & Morency, 2014; Raveendhran & Fast, 2019, 2021), pricing algorithms still harbor privacy concerns regarding the use of personal data (Kim, Barasz, John, & Norton, 2022), which may lead them to perceive such price-setting practices as unfair.

Pricing rules

There are several reasons related to the rules used by pricing algorithms that may lead consumers to perceive their use as unfair. First, if consumers believe that the pricing rules violate the dual entitlement principle (Kahneman, Knetsch, & Thaler, 1986), they may perceive algorithmically set prices to be unfair. In general, this principle suggests that customers are entitled to receive a price at or near their reference price, while companies are entitled to earn their reference profit. This suggests that, if a company increases its price to compensate for increased costs, consumers may view this as fair. However, when an algorithm is used to deploy dynamic pricing, prices often rise independently of cost increases (due to fluctuations in demand, inventory levels, market buying patterns, demographics, etc.; Choi, Song, & Jing, 2023). Consumers may then perceive these price increases as unfair, and therefore, may avoid buying from this seller.

Second, consumers may believe that the algorithm's rules allow for more frequent price changes, and that prices fluctuate more often when set by algorithms instead of humans (Haws & Bearden, 2006). Past research has shown that consumers perceive such frequent changes over short periods to be unfair. More generally, consumers may hold perceptions of unfairness toward companies that use pricing algorithms if they perceive that the rules that the algorithms use allow companies to implement price changes more extensively and in ways that have greater impact than when managers make decisions (Duani et al., 2024).

Finally, consumers' fairness perceptions can also be shaped by their belief about the rules used to set prices in the market more generally. For instance, fairness perceptions and consumer attitudes toward companies using pricing algorithms can be significantly influenced by market norms surrounding dynamic pricing. In markets where dynamic pricing is the norm and many competitors use the technology (e.g., the airline, live entertainment, and hospitality industries), consumers may view price fluctuations more favorably. The same strategy, however, may be perceived differently in markets where frequent price changes are not as common and therefore not expected (e.g., public transportation).

The interviews with the pricing executives highlight that customers' perceptions of price fairness and potential reputational damages are a large concern for managers. *Kevin Bright* (Former Head of Pricing, Europe, McKinsey & Company) sees fairness considerations as more important than other concerns: "It's the reputational risk that is top of mind for them." *Mark Billige* (Chief Executive Officer, Simon-Kucher & Partners) highlights the observation that customers tend not to complain about price level, but rather about price differences over time and compared to other customers: "It's rarely, I think expensive, inexpensive or too much, too little." It's more than someone else or more than it was yesterday." "And that is what people struggle with. I think it's the dynamism of pricing."

Pol Vanaerde (Founder and Chair, European Pricing Platform) recommends two things to avoid potential reputational damage: "First of all, it's important to understand if your customers accept dynamic pricing. The second thing is that in your rule-based pricing, you install guidance when you say you're not going to do things that are unfair or perceived as unfair." *Jean-Manuel Izaret* (Managing Director & Senior Partner; Global Leader, Marketing, Sales & Pricing Practice, Boston Consulting Group) explains that "in our approach, every variable that's about consumer identity is completely out of the algorithms" and that behavioral variables are sufficient: "We think there is enough ability to adjust around behavior without adjusting about who people are."

Dynamic outputs

Consumers' perceptions of price algorithms are affected by their observations or beliefs about the algorithm's outputs. For example, if consumers believe (or observe) that others are paying different prices for the same product or service, they may perceive these algorithmically set prices as unfair (Feinberg, Krishna, & Zhang, 2002; Haws & Bearden, 2006; Kuo, Rice, & Fennell, 2016; Lyn Cox, 2001).

Additionally, consumer's perceptions will depend on other price comparisons they make after obtaining a price. For example, it is reasonable to expect that consumers aware of price fluctuations over time will revisit the websites or stores where they made a purchase and check whether they could have secured a better or worse deal by waiting. Such ongoing price checking may lead to feelings of regret or elation, depending on the outcome (Pizzutti, Gonçalves, & Ferreira, 2022). Regardless of the result, this behavior is likely to cause consumers some stress due to the price uncertainty and lack of closure around pricing. This (dis)satisfaction may also affect important customer behaviors, including product returns, repeat purchases (i.e., customer retention), word of mouth, and referrals or complaints (e.g., on social media).

Summary

For these reasons, algorithmic pricing needs to be integrated with a company's customer relationship management (CRM) systems. This integration involves sharing the input data (e.g., customer purchase history data) as well as the goals of the CRM system (e.g., customer lifetime value (CLV)), which will then inform the pricing algorithm. For example, the algorithm can set comparatively lower prices for products in categories the customer has shown interest in but has yet to purchase, thereby increasing their CLV through cross-selling. To prevent unfavorable price comparisons based on inaccurate recall of past (reference) prices, the algorithm could display current prices relative to the prices the customer has previously paid. Additionally, the algorithm could monitor consumer reactions to the frequency of past price changes, and if feasible, adjust the frequency of those changes to optimize customer satisfaction and minimize unfavorable reactions.

More generally, to address customer perceptions of algorithmic pricing, firms must account for potential violations of fairness norms discussed above by implementing guardrails in their pricing rules, such as limiting price increases during periods of excess demand. Avoiding discriminatory pricing based on demographics such as gender requires not only not using such input data, but also actively monitoring the algorithmic output to ensure the algorithm does not inadvertently learn and replicate discriminatory practices from other data (patterns). Companies need to be transparent about the input data they use and their general pricing rules, and need to continue to monitor consumer reactions to the prices set by algorithms as their use expands in general and within their specific industry.

3.2. Competition

The competitive landscape and the use of algorithmic pricing by competitors may influence a company's decision to adopt algorithmic pricing. In addition, competitors' prices are often a key input to algorithmic pricing, potentially shaping the algorithm's rules (e.g., if price matching is a desirable outcome). *Mark Billige* highlights the risk to focus too much on competitors' prices: "So you get very fixated on prices and I think there's a lot of danger if you follow your competitors' prices too closely and therefore ignoring other differences." Therefore, a firm that just matches competitor prices might neglect other important factors of customers' buying decisions: "It's very hard to benchmark their value or their quality and that's part of the problem which is, we have all these numbers on prices, but we lack similar numbers on quality, perception, value, all this kind of stuff."

An important consideration in the implementation of algorithmic pricing is its impact on competition, particularly with respect to whether the algorithms are designed to mitigate the negative effects of price competition. Potential risks that need to be considered include tacit collusion and firms being trapped in prisoner's dilemmas (see Section 4.1). *Kevin Mitchell* (President, Professional Pricing Society) emphasized the need to think about the strategic implications of using pricing algorithms: “Once you install an algorithm…things don't happen in a vacuum in our space. You're going to make a move with an algorithm. Your marketplace, you know all the seeds, your customer, your competition, your cost might change. What are the effects down the line?”

While studies on algorithmic pricing have shown its short-term effectiveness, the long-term effects of algorithmic pricing on competition remain understudied. Recent studies have suggested the potential for collusive behavior due to the use of similar algorithms by competing firms and algorithms converging on similar pricing strategies (Assad, Clark, Ershov, & Xu, 2024; Brown & MacKay, 2023; Calvano, Calzolari, Denicolò, & Pastorello, 2020; Hansen, Misra, & Pai, 2021; Miklós-Thal & Tucker, 2019). Such a collusive outcome can also emerge in the context of competitive price setting using large language models directly (Fish, Gonczarowski, & Shorrer, 2024). However, it is inconclusive whether this holds true across industries, given the proliferation of algorithms and advances in the methodologies used in algorithms (see Section 4.1 for a more detailed discussion of algorithmic collusion).

Interestingly, our interview partners were less concerned about potential collusion among pricing algorithms and thought it more likely that algorithms would lead to increased price competition. For example, *Jean-Manuel Izaret* observes that “the behaviors you see from algorithms in the market so far tend to be deflationary more than inflationary.” Rather, pricing executives worry that pricing algorithms increase the risk of starting price wars. For example, *Kevin Mitchell* emphasizes that: “we have all seen and heard about instances where price wars started over very, very small pricing moves.” Therefore, the implementation of algorithmic pricing rules must take into account and avoid triggering price wars.

3.3. Company: Organization

Algorithmic pricing can benefit firms by making price-setting processes more efficient and by simplifying managers' pricing decisions. It allows managers and firms to respond more quickly to market changes, especially changes in supply and demand, thereby increasing profits (Ham, He, & Zhang, 2022; J. P. Johnson, Rhodes, & Wildenbeest, 2023). However, the successful implementation of algorithmic pricing must consider managers' perceptions and acceptance of the use of algorithmic pricing, as well as the necessary skills that managers must possess. Algorithms need to effectively align managers' incentives with the firm's objectives (Bertini & Koenigsberg, 2021). In addition, algorithmic pricing needs to be integrated into a firm's organizational structures, processes, and information systems.

In terms of managers' perceptions, it is critical that new tools, such as algorithmic pricing, are introduced across all relevant business functions, and that managers are both persuaded to accept these tools and trained to use them effectively. Managers may be reluctant to adopt algorithms, mirroring the resistance often observed among consumers. Previous research suggests that people may hesitate to choose algorithms over human decision making, even when algorithms consistently outperform humans (Dietvorst, Simmons, & Massey, 2015). This algorithm aversion may be due to a variety of reasons, including the opacity of the AI process (Yeomans, Shah, Mullainathan, & Kleinberg, 2019), a desire for control and the ability to modify (imperfect) algorithms (Dietvorst, Simmons, & Massey, 2018), reluctance to adopt new options, and overconfidence in personal experiences (Diab, Pui, Yankelevich, & Highhouse, 2011; Y. Lu, Wang, Chen, & Xiong, 2023).

To explore these factors, we surveyed 83 pricing managers to understand their perceptions and use of algorithmic pricing (see Section 2.3.2). Our findings reveal that reluctance to adopt pricing algorithms stems from several negative perceptions, including concerns about reduced transparency, the "black box" nature of algorithms, diminished managerial control over pricing decisions, decreased trust, and unfavorable consumer perceptions of fairness. This reluctance is not due to a lack of understanding of their benefits, as pricing managers who did not implement pricing algorithms tend to overestimate their advantages (for further details and analyses related to pricing practices and types of pricing algorithms used, see Web Appendix B).

This relates to the insight of *Kevin Bright* (Former Head of Pricing, Europe, McKinsey & Company) that managers are more likely to adopt pricing algorithms they understand: “My experience has been that most of the models are simpler than they could be because you need that link between the intuition of the decision maker and their ability to see the variables in the model that they would have used themselves.” *Jean-Manuel Izaret* adds that the understanding of the algorithm is also important to be able to communicate prices to customers: “Having transparency for the sales force about why prices are going one way or the other is important because they need to explain it to customers.”

Managers are also likely to be concerned about how adopting algorithms will impact their roles. These types of concerns can lead to reluctance and resistance among managers when weighing the adoption of pricing algorithms. Such concerns can be addressed with a three-pronged approach. First, managers need to be educated and informed about how the algorithm works. The development of explainable AI that demystifies the black-box nature of machine learning algorithms would be helpful in this regard. Second, managers' insights could be incorporated into the algorithm. This can be particularly valuable when historical data are limited. However, care should be taken to avoid introducing human bias into the algorithm. Third, and perhaps most importantly, managers should be invited and actively involved in overseeing the algorithms to mitigate the potential risks of using them. Managers should be encouraged to interact with customers and gather feedback on their reactions to and concerns about pricing algorithms that may not be observable or inferred from revealed customer behavior. Depending on the nature of the concerns uncovered, managers may need to adjust the algorithms.

The aspects of managers' concerns regarding their roles was also raised by the pricing executives we interviewed. *Kevin Mitchell* (President, Professional Pricing Society) highlighted that managers may feel threatened by algorithms: "Sometimes people feel that they're losing a little bit of control over their product, which might from a career perspective, be their baby." He also emphasized the need for (some) human oversight was mentioned several times, especially in case of important customers: "I think for a really big deal, if it's really, really important to the organization, then oversight is important just because there are always in pricing literature examples of algorithms that have basically gone on their own and done their own things that may or may not be completely in line with the company's KPIs." The lack of control over pricing decisions was also a concern indicated in the adoption of pricing algorithms in the survey of pricing managers (see Web Appendix B).

In the *case study*, keeping a "human in the loop" was also a critical issue for the managers involved. In the case study implementation, the managers added several constraints to the price optimization process, such as restrictions on overnight price adjustments, limits on price differences between comparable products, limits on maximum or minimum prices, considerations for price endings, and rules on the frequency of price changes per week.

Relatedly, many two-sided platforms adopt pricing algorithms to assist sellers who often lack managerial capabilities. The efficacy of such algorithms depends not only on their performance but also on their adoption and use by sellers. However, seller skepticism, rooted in a general aversion towards algorithms, presents a barrier. Another challenge is that it may be unclear to sellers whether the algorithm is designed to maximize the platform's revenue or their own. One reason for this is because platforms do not have accurate information on sellers' marginal costs, and therefore, platforms earn a fixed share of sellers' revenues rather than profits. As a result, platforms have an incentive to adopt algorithms that set seller revenue-maximizing prices instead of seller profit-maximizing prices. Therefore, while platforms have an incentive to support sellers' pricing decisions, objectives may not necessarily align with those of the sellers. A key issue to consider when implementing algorithmic pricing rules on two-sided platforms is the potential tension between the revenue goals of the platform and those of third-party sellers.

Finally, using algorithms to make pricing decisions requires coordination with managers responsible for marketing and operational inputs, such as the level of quality built into products and services, inventory levels, promotions, and channel design. Given that some of these decisions, such as inventory levels and promotions, occur frequently, it would be ideal to automate them through an integrated algorithm. Input from the various functional units responsible for these aspects would be critical to the success of such an algorithm. In addition, a company may choose to assign responsibility for the inputs, rules, and outputs of algorithmically determined prices to a single department, rather than dividing these responsibilities among multiple departments, such as IT handling the input data and marketing managing the rules and output. This is increasingly feasible and efficient to implement given the general trend toward digitization of business.

Our interview partners highlighted the question of the organizational embeddedness of algorithmic pricing. *Mark Billige* (Chief Executive Officer, Simon-Kucher & Partners) emphasizes: “Who owns pricing? It is irrelevant whether it's a person that comes up with it or your system comes up with it---someone has to own the pricing decision in the company.” However, it may depend on the status and hierarchy-level of the pricing algorithm owner “people accept the numbers that come out of these systems.” *Pol Vanaerde* adds that: “you need to have your full organization aligned. And that's the biggest challenge that I see in organizations if you start installing algorithm driven pricing, it takes a lot of alignment in your organization. You need your data science team, you need your marketing, you'll need your category managers and your pricing aligned. You need to bring them together and explain what you do with the system.”

Managers must ensure that new tools are effectively adopted across all relevant business functions. Ideally, firms should use the adoption of pricing algorithms as an opportunity to streamline pricing decisions within the organization and improve coordination between different functional units. This requires ongoing monitoring, for example by a corporate oversight committee.

3.4. Company: Marketing Mix

The implementation of algorithmic pricing needs to be integrated into a firm’s marketing mix—price, product, place and promotion—ensuring alignment with broader strategic goals.

3.4.1. Price

Algorithmic pricing must align with the firm’s overall pricing strategy and revenue model, while considering its impact on customer price sensitivity, which in turn affects optimal pricing decisions. Skimming and penetration pricing are important strategic choices for long-term pricing (Spann, Fischer, & Tellis, 2015). For example, a firm's goal may be to gain market share through a penetration pricing strategy, so the pricing algorithm would be set to price competitively relative to competitors' prices. Conversely, a price skimming strategy would factor in the price sensitivity of a target segment of "innovative customers," as well as the predicted product life cycle, to determine the timing for price reductions.

While the use of algorithmic pricing is more straightforward in the case of a pay-per-use revenue model, subscription-based companies can leverage algorithms to determine promotional discounts for new customers, pricing for additional add-on sales not included in the subscription, and to offer targeted discounts to prevent customer churn.

The use of algorithmic pricing can also change the price sensitivity in the market, thereby affecting optimal pricing strategies. For instance, the use of pricing algorithms may alter how frequently or in what manner consumers search for purchase options (e.g., incognito mode; Lagerlöf, 2023) and seek information about prices or other attributes. Since pricing algorithms often consider consumers' online search behavior (e.g., the frequency and duration of website visits), consumers may adjust their search strategies based on the (actual or assumed) rules pricing algorithms follow. Common strategies for airline ticket shoppers, for example, include clearing browser cookies, booking flights on certain days of the week (e.g., Tuesday), or minimizing repeated searches for the same flight.

While past research has shown that consumers' reactions to price depend on deviations from an expected or reference price (Thaler, 1985), dynamic pricing models might affect the strength of reference price effects (Prakash & Spann, 2022), or replace a fixed reference with a reference price distribution. This may lead to more complex patterns of price sensitivity, as consumers' expectations are shaped by both current and previously observed price levels.

3.4.2. Product

The implementation of algorithmic pricing may be more or less suitable for different product types, such as durable vs. consumable products, hedonic vs. utilitarian products, and luxury vs. mainstream products. In addition, the use of algorithmic pricing may affect product quality perceptions and the relative importance consumers place on price compared to other product attributes.

Durable products tend to be purchased less frequently and are generally more expensive (e.g. laptops) than consumables. As a result, consumers tend to be more involved in the decision-making process and make more careful choices when purchasing durable products. Price fluctuations driven by pricing algorithms can be expected to have a more substantial impact in these cases as consumers may choose to wait to get a better deal or use price recommendation tools to (supposedly) improve decision quality. Therefore, the implementation of algorithmic pricing for durable products may provoke stronger behavioral responses from consumers, affecting optimal pricing.

A second product characteristic influencing consumers' reactions to algorithmic pricing is the nature of the product—namely, whether the product is predominantly hedonic or utilitarian (Ratneshwar & Mick, 2013). While hedonic products are mainly driven by sensory or experiential pleasure, utilitarian products are cognitively driven, based on functional and instrumental goals (e.g., lemonade versus sports drink; Botti & McGill, 2011). As consumers are already more driven by immediate rewards and find themselves in a more affect-driven mindset, they may be more inclined to bypass the evaluation process and make quicker purchases when pricing algorithms push reductions on hedonic products. This may not be the case for utilitarian products, as consumers may be more likely to engage in a careful, cognitively driven evaluation of product options.

Third, depending on where they are ranked in the brand hierarchy, companies can be considered luxury or mainstream (Keinan, Crener, & Goor, 2020). Luxury brands often carry symbolic and aspirational meanings (e.g., power, success) and are associated with higher-than-average prices. Importantly, their positioning influences how consumers perceive the company, its products (e.g., perceived quality), and how they evaluate purchases when these companies adopt pricing algorithms. For example, when luxury brands lower their prices through dynamic pricing, consumers may view this as a rare opportunity to own a luxury product (e.g., Hermès purse), skipping the evaluation stage and making an impulsive purchase. More generally, consumers may hold perceptions regarding the frequency of price changes and perceptions of product quality, status, and luxury. For example, while they have already experienced frequent price changes for less expensive household products, they may expect that prices should vary less for high-end luxury products.

The implementation of pricing algorithms can also affect how consumers draw conclusions about product quality. Past research has shown that prices are often (positively) correlated with actual product quality. Thus, it is not irrational for consumers to infer quality from the prices they observe (Rao & Monroe, 1989). However, if prices vary constantly, consumers may be less willing to draw conclusions about product quality from prices. Frequent price changes may lead consumers to infer that price and quality are not necessarily related, and they may turn to other proxies and indicators to judge quality. Alternatively, consumers may make quality inferences not just based on price, but also on price distributions. For example, they may reason that prices that vary less (e.g., an upscale resort hotel) are of higher product quality than those that vary more (e.g., a lower-end budget hotel). In addition, previous research has shown that frequent price promotions may negatively affect perceived brand equity (Erdem, Keane, & Sun, 2008).

More generally, algorithmic pricing may alter how consumers weigh price relative to other product attributes. On one hand, pricing algorithms may increase the salience of price, leading consumers to place greater weight on it, and be more influenced by price than by other product attributes. On the other hand, since evaluating a price or using it as a signal of quality is presumably more challenging with constant variation introduced by pricing algorithms, consumers may de-emphasize price and place more weight on other product features.

3.4.3. Place

Just as with brands, pricing strategies need to align with retail strategies. Some retailers, even in the absence of pricing algorithms, employ frequent price changes, using a form of high-low pricing, while others maintain less varying pricing through EDLP (Everyday Low Pricing; Alba, Mela, Shimp, & Urbany, 1999). Price algorithms facilitate more frequent price changes and the ability to adjust prices for more items at once. However, when and how these changes should be allowed with the rules of the algorithm should be consistent with the retail positioning.

Implementing algorithmic pricing presents unique challenges for companies selling through both online and offline channels. While the digital nature of algorithmic pricing is well-suited for online environments, it requires digital technology in physical stores to facilitate dynamic price changes. One such technology is Electronic Shelf Labels (ESLs), which display prices on small digital screens next to products. ESLs allow for the implementation of dynamic pricing at offline retailers (Aparicio & Misra, 2023), as shown in a case study in collaboration with a consulting company offering artificial intelligence solutions for price setting.

We obtain data from one of their solutions, namely providing ESLs and automating pricing for 225 gift and memorabilia stores in museums, aquariums, and zoos in the United States and Canada. Interestingly, prior to ESLs the stores had a corporate policy of updating pricing no more than two times a year (due to high labor costs to manually update prices). However, adopting the ESL technology allowed the stores to implement numerous price changes for offline products in the shelf just by clicking a button—a compelling example of algorithmic pricing being implemented in the offline channel. Indeed, our evidence indicates that gift stores which increasingly adopted ESLs across categories increased the frequency of price changes. This is consistent with extant literature which utilizes the frequency of price changes to infer adoption or usage of algorithmic pricing (Aparicio & Misra, 2023). The results are reported and discussed in Web Appendix C.

While technology makes it easier to adopt algorithmic pricing, there are numerous managerial and organizational challenges. One of them is that algorithmic pricing may determine different optimal prices for online and offline channels. In particular, retailers may want to charge an offline price premium to account for the higher costs of offline channels. However, previous research has shown that consumers may be unwilling to accept an offline price premium (Homburg, Lauer, & Vomberg, 2019). Therefore, algorithmic pricing that optimizes online and offline prices should consider the maximum price differential customers are willing to accept between channels. In addition, there may be differences in the input data available for both channels, with offline channels likely having less consumer and competitor data.

Although it may be easier for online retailers to identify individual customers, it is likely to be more difficult in physical stores unless customers are members of the firm’s loyalty program. Similarly, the types of customers (and their behaviors) who enter a physical store may differ from those who browse online. Finally, there may be important management frictions or barriers for omnichannel retailers if the algorithms (or inputs and capabilities) differ across channels. For example, a retailer's online assortment may be significantly larger than its offline assortment.

Moreover, online prices often change multiple times throughout the day, and it is unclear whether managers would want to replicate this variability in stores. This means that managers interested in algorithmic pricing should be prepared to deal with a variety of algorithms, decision rules, human-in-the-loop criteria, and data constraints that can vary dramatically between customer touch points.

3.4.4. Promotions

Companies need to be mindful of how and when they communicate their use of algorithmic pricing, as well as how they describe what their algorithms do and the price variations consumers may encounter (Kahneman et al., 1986). For example, a company would likely be better off framing a pricing algorithm in a way that emphasizes that consumers will receive a lower price during periods of low demand, rather than emphasizing the possibility of higher prices during periods of high demand. A recent example of this is the controversy surrounding the use of dynamic pricing at Wendy's.[6] This policy was communicated in the press as Wendy's would be using surge pricing– which led consumers to associate the pricing with higher costs during peak demand. If Wendy's had framed the price differences as an opportunity for lower prices during off-peak hours instead, consumer reactions might have been more favorable.

The implementation of algorithmic pricing also affects how price promotions are utilized. Frequent algorithmic price changes could replace or eliminate traditional price promotions altogether. However, a firm may still be interested in signaling price promotion to consumers, such as highlighting a specific absolute or relative discount (S.-F. S. Chen, Monroe, & Lou, 1998). In such cases, the firm needs to determine how to calculate discounts relative to past dynamic prices, while ensuring compliance with any potential regulatory requirements (Friedman, 2015).

---

[6] See: https://www.inc.com/bruce-crumley/dynamic-pricing-keeps-spreading-despite-protest-from-wendys-customers.html.

Algorithmic pricing can be integrated with other algorithmically driven marketing mix elements, such as digital ad buying and targeting. For example, customer data can be used as input for both algorithmic pricing personalization and ad targeting, while advertising metrics such as click-through rate can be used to evaluate and optimize both pricing and advertising strategies.

4. Key Regulatory Concerns in Algorithmic Pricing Implementation

In recent years, researchers, policymakers, and antitrust agencies worldwide have been examining the opportunities and risks associated with algorithms, particularly pricing algorithms. While algorithms can have pro-competitive effects by enhancing supply-side and demand-side efficiencies (OECD, 2017), they also raise significant concerns among regulators that firms must consider when implementing algorithmic pricing.

A primary concern is their potential to facilitate collusion, resulting in higher prices. This can occur through algorithms that support explicit agreements, hub-and-spoke arrangements where multiple firms rely on the same third-party pricing software, or algorithmic autonomous tacit collusion (Competition & Markets Authority, 2021; Li, Xie, & Feyler, 2021). Additionally, there are concerns about the extent of price discrimination enabled by the availability of vast consumer data and the use of advanced dynamic or personalized pricing algorithms. Table 6 outlines the key implementation features of these algorithms in relation to these regulatory concerns, which we discuss in more detail in the following sections.

Table 6: Regulatory Concerns and Key Implementation Features

Regulatory Concerns		*Key Implementation Features (Inputs, Rules, Outputs)*
Price Collusion	*Algorithms facilitating explicit collusion*	• Input: Shared pricing rules or access to common pricing data. • Rules: Implement coordinated pricing rules via the algorithm or use it to detect and respond to deviations in order to stabilize agreements (e.g., price fixing or resale price maintenance). • Output: Supracompetitive prices aligned with the collusive agreement or retaliatory prices.
	Algorithms in hub-and-spoke settings	• Input: Information exchange facilitated by third-party software. • Rules: Pricing algorithm provided by a central data analytics company. • Output: Potential collusive prices, willingly or not, due to reliance on the same algorithm.
	Algorithmic autonomous tacit collusion	• Input: Data on market conditions and competitor behavior. • Rules: Self-learning algorithms autonomously adapt pricing strategies to avoid competition. • Output: Supracompetitive prices without explicit communication or agreement.
(Unlawful) Price Discrimination	*Dynamic pricing algorithms*	• Input: Real-time demand and supply data. • Rules: Adjust prices dynamically based on market fluctuations without personalizing to individuals. • Output: Dynamic pricing that may inadvertently lead to unfair outcomes for some consumers.
	Personalized pricing algorithms	• Input: Consumer-specific data (e.g., behavior, location, purchasing history). • Rules: Use algorithms to estimate willingness to pay and set individualized prices. • Output: Tailored prices that maximize revenue, with potential risks of discrimination or unfair practices.

4.1. Price Collusion

While the theoretical literature on algorithmic collusion is growing, empirical studies remain limited. On the theoretical front, Calvano et al. (2020) study the potential impact of algorithmic pricing on collusion using simulations. Using a canonical oligopoly model with repeated, simultaneous price competition, they allow each simulated firm to use Q-learning to update their pricing rules. They find that the algorithms consistently learn to charge supracompetitive prices, without communicating with one another. Consistent with theory, the high prices are sustained by collusive strategies with a finite phase of punishment followed by a gradual return to cooperation. Similarly, after documenting heterogeneity among firms in the pricing technology employed and the frequency of price updates for OTC allergy drugs, Brown and MacKay (2023) develop a model in which firms can differ in pricing frequency and adopt pricing algorithms that respond to rivals' prices. Their model and simulation show that, in a competitive (Markov perfect) equilibrium, the introduction of simple pricing algorithms can generate price dispersion, raise price levels, and amplify the price effects of mergers.

More recently, Fish et al. (2024) use Open AI's GPT-4 and conduct experiments with algorithmic pricing agents to demonstrate that Large Language Model (LLM)-based pricing agents quickly and consistently collude in oligopoly settings, even when instructed only to seek long-run profits, with no explicit or implicit suggestion of collusion. Conversely, others argued that algorithmic pricing may improve a firm's price response to demand fluctuations and therefore increase incentives for firms to deviate from collusive prices. This could make collusive pricing less sustainable under algorithmic pricing (Miklós-Thal & Tucker, 2019; O'Connor & Wilson, 2021). Taken together, there is little theoretical certainty that algorithmic price competition would lead to collusive outcomes, but the recent capability of LLM-driven agents raises concerns about algorithmic collusion.

Empirical research has primarily focused on hub-and-spoke settings where multiple firms use the same third-party pricing software. Assad et al. (2024) study the impact of algorithmic pricing in Germany's retail gasoline market. Using instrumental variables to control for the potential endogeneity of the adoption decision, Assad et al. (2024) find that pricing algorithm adoption increases the profit margin in duopoly and triopoly markets, but only if all stations adopt the algorithm. Calder-Wang and Kim (2023) examine algorithmic pricing in property management and find that adoption enables managers to set more responsive prices. Buildings using the software increase prices during booms and lower them during busts compared to non-adopters. Applying a structural housing demand model and a conduct test in the Seattle market, they find limited evidence of coordination. These studies underscore that the mere use of the same pricing algorithm by firms is not sufficient to imply a tacitly coordinated outcome. Beyond collusion, another concern that arises when market players rely on the same algorithms is error propagation, potentially leading to lasting price bubbles even in competitive markets. Fu, Jin, and Liu (2022) study Zillow's Zestimate algorithm and, while highlighting the human-algorithm feedback loop, dismiss concerns about persistent error propagation.

Despite the existing research on algorithmic collusion, its practical feasibility and scale remain uncertain. While the adoption of pricing algorithms has increased, their use is not yet universal, particularly for autonomous systems, and evidence of significant tacit collusion remains lacking. Nonetheless, competition authorities remain vigilant, publishing studies and organizing roundtables on this topic discussing the applicability and limitations of current regulations.[7]

In the United States, many experts argue that the current legal framework is sufficient to assess pricing algorithms collusive behavior. For example, the Sherman Act's Section 1 can impose criminal penalties for explicit collusion. For instance, in November 2023, the DC Attorney General announced a lawsuit alleging that 14 of DC’s largest landlords coordinated through RealPage’s centralized price-setting algorithm to artificially inflate rent prices.[8] Addressing tacit collusion poses a greater challenge, and, at present, the Federal Trade Commission's (FTC) authority under

[7] See OECD (2023) for an extensive list of examples.
[8] Calder-Wang and Kim (2023) study is motivated by a series of class action lawsuits filed against RealPage regarding its use of algorithmic pricing.

Section 5 of the FTC Act, which pertains to prosecuting 'unfair methods of competition,' might be the only existing mechanism to oversee tacit algorithmic collusion. More recently, in the United States, new bills have been proposed to strengthen enforcement under the Sherman Act and the FTC Act. For example, on January 30, 2024, Senator Amy Klobuchar (D-MN), Chair of the Senate Subcommittee on Competition Policy, introduced the *Preventing Algorithmic Collusion Act* to prohibit the use of pricing algorithms that facilitate collusion.[9]

In Europe, both the European Union (European Union, 2017) and the United Kingdom (OECD, 2017) largely share the United States' position on algorithmic pricing, recognizing that most concerns can be effectively addressed within the existing competition law framework. For example, in 2018, the European Commission utilized existing antitrust legislation (namely, Article 101 TFEU), to penalize Asus, Denon & Marantz, Philips, and Pioneer for engaging in resale price maintenance tactics enabled by price comparison websites and specialized pricing platforms. These tools enabled the manufacturers to monitor online retailers' pricing, identify discrepancies, and enforce minimum retail prices.[10]

While existing tools may be sufficient to address algorithms that facilitate collusive agreements, the OECD and other regulators recognize perceived shortcomings in current legislation, particularly regarding mechanisms to address cases involving a lack of explicit communication.

4.2. (Unlawful) Price Discrimination

Price discrimination is often regarded by economists as a way to enhance market efficiency, particularly as it approaches first-degree price discrimination. While not inherently

[9] United States' legislators are also moving to adopt laws that prevent or regulate the use of algorithmic pricing in specific sectors. For example, two House representatives introduced the Preventing Algorithmic Facilitation of Rental Housing Cartels Act on 6 June 2024, which would prohibit digital price-fixing by landlords.

[10] See https://ec.europa.eu/competition/antitrust/cases/dec_docs/40465/40465_337_3.pdf

illegal, it becomes prohibited when accompanied by anticompetitive, unfair, or deceptive practices. The use of pricing algorithms, combined with the increasing availability of customer data, has made price discrimination more feasible, drawing greater legislative and regulatory scrutiny.

Algorithmic price discrimination can result from dynamic pricing, which adjusts prices in real time based on fluctuations in supply and demand, or personalized pricing, which adjusts prices based on individual consumer information or behavior, such as search history, location, or device.

4.2.1. Dynamic Pricing

Because dynamic pricing can optimize prices based on real-time market conditions such as demand, it can be harmful, by potentially enabling the exploitation of consumers and creating a perception of unfairness. For example, during unusual events that disrupt markets, such as floods (Crane, 2023), bombings, and terrorist attacks (Roberts, 2016), prices for car share rides for companies like Uber and Lyft rose to much higher levels than were usually experienced in the market. Other examples of "price gouging" include the high observed prices of flights and water sold through online markets before an approaching hurricane (Popomaronis, 2017). Although some firms impose price caps during emergencies and override their dynamic pricing algorithms (Mutzabaugh, 2017), or explore alternative solutions to balance supply and demand, such as offering higher compensation to car share drivers during emergencies (Carlson, 2012), these practices are not always implemented and their effectiveness can vary. In other situations, there may be concerns that dynamic pricing might disproportionately adversely affect lower income or other disadvantaged consumers. For example, when dynamic pricing is used for energy prices, it could be that lower income consumers might have less flexibility for reducing their energy use (e.g., seniors who need to use air conditioning for their health) or shifting their use to lower priced times such as nights (e.g., if lower income individuals are more likely to work at those times).

Charging "excessive" prices constitutes an abuse of dominance in many countries, including almost all OECD members; for example, under EU competition law, agencies can sanction dominant firms for using their market power to exploit consumers directly through Article 102 TFEU. In the United States, excessive prices per se are not a matter of federal competition enforcement, but many states have laws that regulate price gouging by limiting price increases for essential goods and services, such as gasoline during emergencies.[11]

4.2.2. Personalized Pricing and Data Privacy

While personalized pricing does not seem to be as widespread as dynamic pricing, advancements in technology and the increasing availability of customer data have made it more feasible and, consequently, a focus of legislative and regulatory scrutiny.[12, 13]

Traditionally, the economics literature identifies three cumulative conditions for effective price discrimination, all of which apply to personalized pricing: firms must have some degree of market power, consumers must exhibit heterogeneity in willingness to pay that firms can identify, and businesses need a mechanism to measure consumers' willingness to pay. Additionally, there must be no arbitrage among buyers. Among these, the ability of firms to measure consumer

[11] Despite the efforts of existing state laws to curb price gouging, concerns persist regarding their ability to effectively address algorithmic price gouging practices, primarily due to the fact that these laws were enacted primarily before the emergence of algorithmic pricing and digital commerce (K. R. Williams (2022).

[12] For an overview of the evidence on the practical occurrence of personalized pricing, see Rott, Strycharz, and Alleweldt (2022).

[13] The OECD defines personalized pricing as "any practice of price discriminating final consumers based on their personal characteristics and conduct, resulting in each consumer being charged a price that is a function – but not necessarily equal – to his or her willingness to pay;" (OECD (2018)). This means that personalized pricing is not limited to perfect or first-degree price discrimination but can also encompass second- and third-degree price discrimination. However, with increasingly accurate and accessible data on customer characteristics, particularly for digital companies, adopting first-degree price discrimination and charging each consumer his or her exact willingness to pay, enabling the firm to capture the entire consumer surplus is becoming more feasible (Ezrachi and Stucke (2016)).

willingness to pay has grown significantly in recent years, driving concerns about the risks associated with personalized pricing.[14]

Economists have studied the impact of price discrimination in both monopoly and imperfectly competitive markets (see Verboven (2016), for a review of the literature on price discrimination and Botta and Wiedemann (2019), for a discussion in the digital context). This research highlights that personalized pricing can, on the one hand, substantially improve allocative efficiency by enabling companies to serve low-end consumers who would otherwise be underserved. On the other hand, its effects on distributional outcomes—across firms and different types of consumers—and on dynamic efficiency remain unclear, as such practices can promote both innovation and rent-seeking behavior. Using two randomized field experiments on ZipRecruiter, Dubé and Misra (2023) are the first to document both the feasibility and implications of scalable personalized pricing. They find that personalized pricing can improve expected profits by 19 percent relative to the uniform price that is optimized to reflect the firm's market power, and by 86 percent relative to the nonoptimized uniform price. While total consumer surplus decreases under personalized pricing, they show that over 60 percent of consumers benefit from personalization. Under some inequity-averse welfare functions, they find that consumer welfare may even increase with personalized pricing.

While the effect of price discrimination on consumers' welfare is ambiguous, research suggests that, while consumers may accept traditional forms of price discrimination, such as third-degree price discrimination (e.g., age-based discounts), they tend to be less receptive to personalized pricing. This resistance is largely attributed to perceived fairness concerns and a lack

[14] Personalized pricing requires some market power, as perfectly competitive markets drive prices down to marginal costs. It is, however, not limited to monopolies and is feasible in markets with economies of scale, scope, network effects, entry costs, or switching costs, which allow firms to charge prices above marginal cost.

of transparency in pricing algorithms. Consumers may view personalized pricing as unfair, as it can lead to different prices for identical products or services. Furthermore, the opacity of pricing algorithms can erode consumer trust and satisfaction (Xia, Chatterjee, & May, 2019; Zuiderveen Borgesius & Poort, 2017). See also Section 3.1 for the detailed discussion of fairness perceptions.

In addition to concerns about consumer welfare, fairness, and transparency, Cheng and Nowag (2022) argue that personalized algorithmic pricing can also enable firms to engage in harmful exclusionary business practices. Through the use of predatory pricing, rebates, tying, and bundling, firms can limit or exclude competitors from the market, thus engaging in anti-competitive conduct. Personalized pricing makes it easier for incumbent firms to implement predatory strategies by targeting specific customer segments that pose a threat to their market position. By focusing on the entrant's strongest customer groups while maintaining control over their own, incumbent firms can minimize losses and effectively deter competition.

Considering this body of research, personalized pricing presents policymakers with the challenge of balancing competing goals. On one hand, it can expand market access for consumers with lower willingness to pay. On the other hand, it raises concerns about fairness, transparency, and potential discrimination. Consumers often perceive personalized pricing as unfair, particularly when the criteria for pricing decisions are unclear, which can undermine trust in digital markets. Moreover, unjustifiable forms of discrimination, such as price differences based on race or gender, cannot be ruled out.

The risks of personalized pricing can be addressed through a combination of policies and legal instruments. Privacy and data protection laws, which govern the collection, storage, and processing of personal data, indirectly affect pricing practices, particularly personalized pricing, which relies on the ability to gather and analyze consumer data to set individualized prices.[15] Under the European Union's General Data Protection Regulation (GDPR), the use of personal data, including internet identifiers, for price personalization must adhere to the principles of transparency, fairness, and lawfulness. Processing sensitive data, such as racial or ethnic origin, political opinions, health, or sexual orientation, is generally prohibited for price personalization unless the individual provides explicit consent. The GDPR also grants individuals the right not to be subject to decisions based solely on automated processing, including profiling, that produce significant or legal effects— though such processing is permitted with explicit consent. Countries such as Australia, Brazil, Canada, China, India, Israel, Japan, South Africa, South Korea, Switzerland, Turkey, and the UK have enacted similar data privacy laws (Zafar, 2023).

In the United States, various federal and state laws protect sensitive data that could influence personalized pricing. For example, the Equal Credit Opportunity Act (ECOA), enforced by the FTC, prohibits credit discrimination based on race, color, religion, sex, or other protected characteristics. Regulators have also introduced tools like “algorithmic disgorgement” to adapt to the rise of artificial intelligence. Since 2019, this penalty has required companies to delete machine learning models and algorithms developed using improperly obtained data, such as children’s location data collected without parental consent.[16]

However, even if an algorithm does not explicitly use protected characteristics like race, discrimination may still occur. This can happen when correlations exist between a person’s protected attributes and their behaviors or other features in the data, leading to biased outcomes (Ascarza & Israeli, 2022).

---

[15] Dube et al. (2024) provide a perspective based on the academic marketing literature that evaluates the various benefits and costs of existing and pending government regulations and corporate privacy policies.

[16] See Kate Kaye, The FTC’s New Enforcement Weapon Spells Death for Algorithms, PROTOCOL (Mar. 14, 2022), https://www.protocol.com/policy/ftc-algorithm-destroy-data- privacy.

Complementing privacy and data protection laws, disclosure regulations play a role in mitigating unfair personalized pricing practices. For instance, the GDPR requires data controllers to inform individuals about automated decision-making, including the logic involved and its potential consequences. However, as noted by Rott et al. (2022), this information is typically provided when personal data is collected, not when it is used. Furthermore, such disclosures are often buried in privacy notices that most consumers neither read nor recall, making them ineffective by the time personalized prices are presented.

The Modernization Directive, adopted in 2019 and implemented in mid-2022, introduced significant updates to EU consumer protection law. Under the Consumer Rights Directive (CRD), it mandates that traders disclose the use of personalized pricing based on automated decision-making at the point of sale. This complements the GDPR by ensuring a minimum level of transparency during transactions. The updated CRD has demonstrated some effectiveness. For example, Tinder, following a dialogue with the European Commission, committed to informing consumers by mid-April 2024 about the use of automated means for personalized discounts, including age-based pricing, and to explain the reasons for such discounts, such as consumers' lack of interest in premium services at standard rates.

However, the scope of the Modernization Directive is limited. It excludes contracts related to healthcare, social services, gambling, financial services, real estate, passenger transport, package travel, and food or beverage delivery to consumers' homes. Additionally, the disclosure requirements apply only to distance selling and off-premises contracts and do not cover dynamic pricing techniques unless they involve automated decision-making based on personal data. Moreover, traders are not required to disclose the parameters used to personalize prices—only that the price has been personalized.

More broadly, the effectiveness of disclosure requirements remains questionable. A 2021 OECD study, based on lab experiments in Ireland and Chile, found that online disclosures have limited impact on consumers' ability to identify and comprehend personalized pricing and do not significantly influence purchasing behavior (OECD, 2021).

Lastly, exclusionary business practices and other anticompetitive effects of price discrimination can be addressed within the framework of competition law. In the United States, the Sherman Antitrust Act and subsequent legislation, such as the Robinson-Patman Act of 1936, provide mechanisms to regulate such practices. Similarly, Article 102 of the TFEU in the European Union prohibits abuses of dominant market positions, including certain forms of discriminatory pricing. However, these rules are typically limited to firms with significant market power, which—while likely aligning with the circumstances where personalized pricing is most problematic—may limit their applicability to broader concerns around personalized pricing.

5. Conclusion and Research Priorities

In this paper, we define algorithmic pricing and clarify its relationship with other forms of pricing, such as dynamic and participative pricing. We explore the issues and challenges associated with the strategic alignment of algorithmic pricing with respect to customers, competition, and the firm, i.e., its organization and marketing mix, and the consideration of key regulatory concerns. In addition, we provide empirical support for issues related to the implementation of algorithmic pricing through interviews with pricing executives, a survey of pricing managers, and a case study.

Our discussion highlights the many interdependencies of algorithmic pricing with a firm's marketing strategy and regulatory concerns. Our empirical evidence shows that while firms seem to recognize the potential of algorithmic pricing, they face organizational and implementation challenges. In addition, firms are particularly concerned about customer reactions to the implementation of algorithmic pricing. Interestingly, these concerns seem to mitigate some of the key regulatory concerns. For example, fears of customer backlash likely limit firms' use of unfair algorithmic pricing practices, including discriminatory use of consumer data. Additionally, managers expect pricing algorithms to foster competition and lower prices rather than promote collusive behavior.

We next outline questions and priorities for future research related to algorithmic pricing, which we structure based on our discussions in Section 3 and 4, and in line with Figure 1. See Table 7 below for a summary of the key research priorities.

In particular, we identify five research priorities related to customers and algorithmic pricing: (i) customers' perceptions of the use of algorithmic pricing and the price levels resulting from its use. In addition, it is important to understand how these perceptions evolve as the use of algorithmic pricing increases. Future research can explore how customers' perceptions of algorithmic pricing change over time and across industries, with changes in the overall price level (i.e., whether prices are increasing or decreasing on average) and the degree of price dispersion (i.e., whether there is a lot of variation in prices paid across customers over time and/or at a point in time) as important moderators. (ii) The effect of transparency regarding the use and specific features of pricing algorithms on customer perceptions of algorithmic pricing. Future research can examine how customer perceptions of the fairness of algorithmic pricing across firms and industries are affected by firms' transparency and communication about the use of algorithmic pricing, and how these perceptions evolve over time. Future research may help to better understand the extent to which disclosure of the use of algorithmic pricing affects consumer decisions. Another promising area for transparency-related research is how GenAI can be used to better explain the results of algorithmic pricing to customers and enhance customers’ perceptions. For example, *Jean-Manuel Izaret* suggests adding GenAI as an additional layer of explanation: "GenAI is now becoming a tool to help explain what the algorithms are doing and make it more accessible. Pricing algorithms that make millions of pricing decisions, tend to be quite opaque, it's hard to understand what's happening."

(iii) The impact of algorithmic pricing on consumers' quality inferences from prices across product categories. Future research may measure price-quality inferences for different product categories, considering firms' use of algorithmic pricing in those categories (e.g., the price of a bottle of wine), or of a meal at a restaurant that uses algorithmic pricing vs. one that does not. (iv) The impact of algorithmic pricing on reference prices and price sensitivity. Future research can experimentally test the impact of different degrees of pricing automation on consumers' price sensitivity and (ability to form) reference prices. (v) Future research can test the effect of a firm's use of algorithmic pricing on consumers' perceptions of and loyalty to a brand, considering both the firm's actual implementation and its transparency about the practice (e.g., whether algorithmic pricing increases price search and sensitivity, leading to higher chances of switching and reduced loyalty).

With respect to the impact of algorithmic pricing on competition, future research needs to (vi) examine the longer-term impact of pricing algorithms on market structure, price levels, price dispersion and firms' profitability. This will allow testing whether managers' expectations that pricing algorithms will increase competition rather than facilitate collusive behavior are correct. Related, future research can assess how mangers react to the competitive aspects of algorithmic pricing in their preferences for different competitive strategies. In addition, future research needs to (vii) examine the risk of firms inadvertently colluding, as pricing algorithms may enable new forms of collusion that firms are unaware of.

With respect to the alignment of algorithmic pricing within the organization, we recommend future research to (viii) examine the antecedents and moderators of managers' potential aversion to pricing algorithms. The results of the survey and the interviews provide some insights into what factors impact the adoption of pricing algorithms, including managers' reduced transparency and control over pricing decisions, along with negative consumer perceptions. However, further verification is required. Future research should also (ix) investigate the optimal level and type of managerial input and its implications for data requirements. This is in particular relevant given that only a little over half of the companies in our survey did use information about competing firm's prices and past consumer behavior. It is essential to study the importance of incorporating such information sources. Finally, future research should (x) examine whether firms need to adopt institutional and technical measures to prevent discriminatory and anticompetitive outcomes of algorithmic pricing. Relatedly, firms need to assess the implications for organizational governance as decision-making shifts to pricing algorithms, with a particular focus on adjustments to accountability and (internal) oversight.

With respect to the marketing mix, future research can (xi) study the prevalence of different types of pricing algorithms (dynamic vs. personalized, vs. both) and how they have evolved over time. This may require the development of empirical methods to investigate the use of such algorithms. Future research can (xii) quantify the effectiveness of algorithmic pricing in different industries (including business vs. consumer markets), geographic locations, and online versus offline markets. Further, future research needs to study (xiii) how algorithmic pricing models can align with the increasing use of subscription-based revenue models, for example regarding digital products such as content streaming or digital feature subscription in cars (e.g., extended battery range).

From a regulatory perspective, future studies are needed to (xiv) conduct additional tests across markets to examine whether algorithmic price collusion exists. This may require the development of new tools to detect algorithmic collusion.[17] Further, future research needs to study the longer-term impact of pricing algorithms on competition, price levels, price dispersion, firm profitability, and consumer welfare.

(xv) Future research needs to examine the potential anticompetitive effects of dynamic or personalized pricing, and of different types of pricing algorithms (such as "Win-Continue Lose-Reverse" rule and Adaptive machine learning). For example, incumbents may use personalized pricing to minimize losses and effectively deter competition by focusing on an entrant's strongest customer groups while maintaining control over their own. In addition, future research can examine whether, as has been shown for ranking algorithms, algorithmic pricing can lead to self-preferencing, thereby excluding competitors. Further, firms and researchers need to assess the impact of emerging regulations (e.g., regulations in the EU, the US and China) on the adoption, conduct and performance of pricing algorithms.

(xvi) Future research can explore potential trade-offs between data requirements for the efficient use of pricing algorithms and privacy or other data regulations, including the benefits and costs of pricing algorithms versus other non-pricing algorithms that use personal data (for example personalized search ranking, personalized advertising, and personalized product recommendation). In addition, future research can explore the impact of data provided by consumers at the point of purchase and assess the influence of third-party data or consumer profiles on (personalized) pricing.

[17] Existing tools and methods used by for algorithmic auditing are discussed in detail in OECD (2023).

Table 7: Key research priorities for algorithmic pricing

Customers	
(i) Adoption and perceptions	How does the increasing adoption of algorithmic pricing affect customer perceptions?
(ii) Transparency and perceptions	How does transparency about algorithmic pricing affect customers' (fairness) perceptions of pricing algorithms and their decisions? How can GenAI help to explain algorithmically determined prices?
(iii) Price-quality relationships	How does algorithmic pricing change consumers' quality inferences from prices (for different product categories)?
(iv) Reference price effects and price sensitivity	How does algorithmic pricing affect reference price formation and price sensitivity?
(v) Brand loyalty	Does algorithmic pricing affect consumers' brand loyalty?
Competition	
(vi) Long-term impact on Competition	Longer-term impact of pricing algorithms on market structure, price levels, price dispersion and firms' profitability
(vii) Risk of collusion	Examine firm's risk of inadvertently colluding
Company: Organization	
(viii) Algorithmic aversion of managers	Antecedents and moderators of managers aversion towards algorithms that inhibit their use
(ix) Input to pricing algorithms	(Optimal) level and type of managerial input and data requirements
(x) Organizational governance and (internal) oversight	Should firms establish institutional and technical policies to avoid discriminatory and anticompetitive outcomes of algorithmic pricing?
Company: Marketing mix	
(xi) Prevalence of pricing algorithms	Studying the prevalence of different types of pricing algorithms (dynamic vs. personalized, vs. both) and their evolution over time
(xii) Effectiveness of algorithmic pricing	Studying the effectiveness of algorithmic pricing across industries (including business vs. consumer markets), geographic locations, and online vs. offline markets
(xiii) Revenue model alignment	How to align algorithmic pricing with subscription-based models?
Regulatory concerns and possible actions	
(xiv) Collusion	Conduct empirical tests of potential price collusion and studying longer-term impact of pricing algorithms on competitive behavior Development of new tools for algorithmic auditing
(xv) Price discrimination and anti-competitive behavior.	Study potential anticompetitive effects of dynamic or personalized prices, such as self-preferencing. Assess the impact of new regulations on conduct and performance of pricing algorithms
(xvi) Data requirements and privacy regulation	Study the trade-off between data requirements for efficient use of pricing algorithms and privacy regulation Assess the influence of third-party data on pricing

References

Alba, J. W., Mela, C. F., Shimp, T. A., & Urbany, J. E. (1999). The Effect of Discount Frequency and Depth on Consumer Price Judgments. *Journal of Consumer Research*, *26*(2), 99–114. https://doi.org/10.1086/209553

Aparicio, D., & Misra, K. (2023). Artificial Intelligence and Pricing. In K. Sudhir & O. Toubia (Eds.), *Review of Marketing Research. Artificial Intelligence in Marketing* (pp. 103–124). Emerald Publishing Limited. https://doi.org/10.1108/S1548-643520230000020005

Ascarza, E., & Israeli, A. (2022). Eliminating unintended bias in personalized policies using bias-eliminating adapted trees (BEAT). *Proceedings of the National Academy of Sciences of the United States of America*, *119*(11), e2115293119. https://doi.org/10.1073/pnas.2115293119

Assad, S., Clark, R., Ershov, D., & Xu, L. (2024). Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market. *The Journal of Political Economy*, 0. https://doi.org/10.1086/726906

Barocas, S., & Selbst, A. D. (2016). Big Data's Disparate Impact. *California Law Review*, *104*(3), 671–732.

Bertini, M., & Koenigsberg, O. (2021). The Pitfalls of Pricing Algorithms: Be Mindful of How They Can Hurt Your Brand. *Harvard Business Review*, *99*(5), 74–83. Retrieved from https://hbr.org/2021/09/the-pitfalls-of-pricing-algorithms

Botta, M., & Wiedemann, K. (2019). Exploitative Conducts in Digital Markets: Time for a Discussion after the Facebook Decision. *Journal of European Competition Law & Practice*, *10*(8), 465–478. https://doi.org/10.1093/jeclap/lpz064

Botti, S., & McGill, A. L. (2011). The Locus of Choice: Personal Causality and Satisfaction with Hedonic and Utilitarian Decisions. *Journal of Consumer Research*, *37*(6), 1065–1078. https://doi.org/10.1086/656570

Brown, Z. Y., & MacKay, A. (2023). Competition in Pricing Algorithms. *American Economic Journal: Microeconomics*, *15*(2), 109–156. https://doi.org/10.1257/mic.20210158

Calder-Wang, S., & Kim, G. H. (2023). Coordinated vs Efficient Prices: The Impact of Algorithmic Pricing on Multifamily Rental Markets. *SSRN Electronic Journal*. Advance online publication. https://doi.org/10.2139/ssrn.4403058

Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2019). Algorithmic Pricing What Implications for Competition Policy? *Review of Industrial Organization*, *55*(1), 155–171. https://doi.org/10.1007/s11151-019-09689-3

Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2020). Artificial Intelligence, Algorithmic Pricing, and Collusion. *American Economic Review*, *110*(10), 3267–3297. https://doi.org/10.1257/aer.20190623

Campbell, M. C. (2007). "Says Who? !" How the Source of Price Information and Affect Influence Perceived Price (Un)fairness. *Journal of Marketing Research*, *44*(2), 261–271.

Carlson, N. (2012). How A Sandy-Related PR Nightmare Cost Startup Uber $100,000 In A Day. *Business Insider*. Retrieved from https://www.businessinsider.com/how-sandy-related-pr-nightmare-cost-startup-uber-100000-in-a-day-2012-11

Chen, L., Mislove, A., & Wilson, C. (2016). An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace. In J. Bourdeau, J. A. Hendler, R. N. Nkambou, I. Horrocks, & B. Y. Zhao (Eds.), *Proceedings of the 25th International Conference on World Wide Web - WWW '16* (pp. 1339–1349). New York, New York, USA: ACM Press. https://doi.org/10.1145/2872427.2883089

Chen, S.-F. S., Monroe, K. B., & Lou, Y.-C. (1998). The effects of framing price promotion messages on consumers' perceptions and purchase intentions. *Journal of Retailing*, *74*(3), 353–372. https://doi.org/10.1016/S0022-4359(99)80100-6

Cheng, T. K., & Nowag, J. (2022). Algorithmic Predation and Exclusion: LundLawCompWP. Retrieved from https://hub.hku.hk/bitstream/10722/311575/1/content.pdf?accept=1

Choi, S., Song, M., & Jing, L. (2023). Let your algorithm shine: The impact of algorithmic cues on consumer perceptions of price discrimination. *Tourism Management*, *99*, 104792. https://doi.org/10.1016/j.tourman.2023.104792

Cohen, P., Hahn, R., Hall, J., Levitt, S., & Metcalfe, R. (2016). *Using Big Data to Estimate Consumer Surplus: The Case of Uber*. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w22627

Competition & Markets Authority (2021). Algorithms: How They Can Reduce Competition and Harm Consumers. Retrieved from https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers

Crane, E. (2023). Uber, Lyft Ripped for Surging NYC Prices during Storm, Flooding: 'Slime Balls'. *New York Post*. Retrieved from https://nypost.com/2023/09/29/new-yorkers-rip-uber-lyft-for-surging-prices-during-storm/

Diab, D. L., Pui, S.-Y., Yankelevich, M., & Highhouse, S. (2011). Lay Perceptions of Selection Decision Aids in US and Non-US Samples. *International Journal of Selection and Assessment*, *19*(2), 209–216. https://doi.org/10.1111/j.1468-2389.2011.00548.x

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology. General*, *144*(1), 114–126. https://doi.org/10.1037/xge0000033

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

Duani, N., Barasch, A., & Morwitz, V. (2024). Demographic Pricing in the Digital Age: Assessing Fairness Perceptions in Algorithmic versus Human-Based Price Discrimination. *Journal of the Association for Consumer Research.* Advance online publication. https://doi.org/10.1086/729440

Dube, J.-P. H., Bergemann, D., Demirer, M., Goldfarb, A., Johnson, G., Lambrecht, A., . . . Lynch, J. G. (2024). The Intended and Unintended Consequences of Privacy Regulation for Consumer Marketing: A Marketing Science Institute Report. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.4847653

Dubé, J.-P., & Misra, S. (2023). Personalized Pricing and Consumer Welfare. *The Journal of Political Economy*, *131*(1), 131–189. https://doi.org/10.1086/720793

Elmaghraby, W., & Keskinocak, P. (2003). Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future Directions. *Management Science*, *49*(10), 1287–1309. https://doi.org/10.1287/mnsc.49.10.1287.17315

Erdem, T., Keane, M. P., & Sun, B. (2008). A Dynamic Model of Brand Choice When Price and Advertising Signal Product Quality. *Marketing Science*, *27*(6), 1111–1125. https://doi.org/10.1287/mksc.1080.0362

European Union (2017). Algorithms and Collusion - Note from the European Union. Retrieved from https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf

Ezrachi, A., & Stucke, M. E. (2016). *Virtual Competition*. Harvard University Press. https://doi.org/10.4159/9780674973336

Fantini, F., & Das Narayandas (2023). Analytics for Marketers: When to Rely on Algorithms and When to Trust Your Gut. *Harvard Business Review*, *101*(3), 82–91. Retrieved from https://hbr.org/2023/05/analytics-for-marketers

Feinberg, F. M., Krishna, A., & Zhang, Z. J. (2002). Do we care what others Get? A Behaviorist Approach to Targeted Promotions. *Journal of Marketing Research*, *39*(3), 277–291. https://doi.org/10.1509/jmkr.39.3.277.19108

Fish, S., Gonczarowski, Y. A., & Shorrer, R. I. (2024). *Algorithmic Collusion by Large Language Models*. arXiv. https://doi.org/10.48550/arXiv.2404.00806

Friedman, D. A. (2015). Reconsidering Fictitious Pricing. *Minnesota Law Review*, *100*, 921–982.

Fu, R., Jin, G. Z., & Liu, M. (2022). *Does Human-algorithm Feedback Loop Lead to Error Propagation? Evidence from Zillow's Zestimate*. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w29880

Gabel, S., & Guhl, D. (2022). Comparing the effectiveness of rewards and individually targeted coupons in loyalty programs. *Journal of Retailing*, *98*(3), 395–411. https://doi.org/10.1016/j.jretai.2021.08.001

Hansen, K. T., Misra, K., & Pai, M. M. (2021). Frontiers: Algorithmic Collusion: Supra-competitive Prices via Independent Algorithms. *Marketing Science*, *40*(1), 1–12. https://doi.org/10.1287/mksc.2020.1276

Haws, K. L., & Bearden, W. O. (2006). Dynamic Pricing and Consumer Fairness Perceptions. *Journal of Consumer Research*, *33*(3), 304–311. https://doi.org/10.1086/508435

Hill, D. (2015). The Secret of Airbnb's Pricing Algorithm. *IEEE Spectrum*. Retrieved from https://spectrum.ieee.org/computing/software/the-secret-of-airbnbs-pricing-algorithm

Homburg, C., Lauer, K., & Vomberg, A. (2019). The Multichannel Pricing Dilemma: Do Consumers Accept Higher Offline Than Online Prices? *International Journal of Research in Marketing*, *36*(4), 597–612. https://doi.org/10.1016/j.ijresmar.2019.01.006

Kahneman, D., Knetsch, J., & Thaler, R. (1986). Fairness as a Constraint on Profit Seeking: Entitlements in the Market. *American Economic Review*, *76*(4), 728–741.

Keinan, A., Crener, S., & Goor, D. (2020). Luxury and environmental responsibility. In F. Morhart, K. Wilcox, & S. Czellar (Eds.), *Research Handbook on Luxury Branding*. Edward Elgar Publishing. https://doi.org/10.4337/9781786436351.00031

Kim, T., Barasz, K., John, L. K., & Norton, M. I. (2022). When Identity-Based Appeals Alienate Consumers. *Harvard Business School NOM Unit Working Paper No. 19-086*.

Kopalle, P. K., Pauwels, K., Akella, L. Y., & Gangwar, M. (2023). Dynamic pricing: Definition, implications for managers, and future research directions. *Journal of Retailing*, *99*(4), 580–593. https://doi.org/10.1016/j.jretai.2023.11.003

Kuo, A., Rice, D. H., & Fennell, P. (2016). How fitting! The influence of fence-context fit on price discrimination fairness. *Journal of Business Research*, *69*(8), 2634–2640. https://doi.org/10.1016/j.jbusres.2016.04.020

Lagerlöf, J. N. (2023). Surfing incognito: Welfare effects of anonymous shopping. *International Journal of Industrial Organization*, *87*, 102917. https://doi.org/10.1016/j.ijindorg.2022.102917

Li, S., Xie, C. C., & Feyler, E. (2021). Algorithms & Antitrust: An Overview of EU and National Case Law. Retrieved from https://www.concurrences.com/en/bulletin/special-issues/algorithms-competition/algorithms-antitrust-an-overview-of-eu-and-national-case-law

Lu, S., Yao, D., Chen, X., & Grewal, R. (2021). Do Larger Audiences Generate Greater Revenues Under Pay What You Want? Evidence from a Live Streaming Platform. *Marketing Science*, *40*(5), 964–984. https://doi.org/10.1287/mksc.2021.1292

Lu, Y., Wang, Y., Chen, Y., & Xiong, Y. (2023). The role of data-based intelligence and experience on time efficiency of taxi drivers: An empirical investigation using large-scale sensor data. *Production and Operations Management*, *32*(11), 3665–3682. https://doi.org/10.1111/poms.14056

Lucas, G. M., Gratch, J., King, A., & Morency, L.-P. (2014). It's only a computer: Virtual humans increase willingness to disclose. *Computers in Human Behavior*, *37*, 94–100. https://doi.org/10.1016/j.chb.2014.04.043

Lyn Cox, J. (2001). Can differential prices be fair? *Journal of Product & Brand Management*, *10*(5), 264–275. https://doi.org/10.1108/10610420110401829

Miklós-Thal, J., & Tucker, C. (2019). Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers? *Management Science*, *65*(4), 1552–1561. https://doi.org/10.1287/mnsc.2019.3287

Mutzabaugh, B. (2017). Airlines Cap Fares Starting at $99 from Florida Amid Price Gouging Complaints. *USA Today*. Retrieved from https://www.usatoday.com/story/travel/flights/todayinthesky/2017/09/06/airlines-cap-fares-florida-amid-price-gouging-complaints/640332001/

O'Connor, J., & Wilson, N. E. (2021). Reduced demand uncertainty and the sustainability of collusion: How AI could affect competition. *Information Economics and Policy*, *54*, 100882. https://doi.org/10.1016/j.infoecopol.2020.100882

OECD (2017). Algorithms and Collusion - Note from the United Kingdom. Retrieved from https://one.oecd.org/document/DAF/COMP/WD(2017)19/en/pdf

OECD (2018). Personalised Pricing in the Digital Era: Background Note by the Secretariat. Retrieved from https://one.oecd.org/document/DAF/COMP(2018)13/en/pdf

OECD (2021). The effects of online disclosure about personalised pricing on consumers: Results from a lab experiment in Ireland and Chile. Retrieved from https://www.oecd.org/en/publications/the-effects-of-online-disclosure-about-personalised-pricing-on-consumers_1ce1de63-en.html

OECD (2023). Algorithmic Competition: OECD Competition Policy Roundtable Background Note. Retrieved from www.oecd.org/daf/competition/algorithmic-competition-2023.pdf

Pizzutti, C., Gonçalves, R., & Ferreira, M. (2022). Information search behavior at the post-purchase stage of the customer journey. *Journal of the Academy of Marketing Science*, *50*(5), 981–1010. https://doi.org/10.1007/s11747-022-00864-9

Popomaronis, T. (2017). Amid Preparations For Hurricane Irma, Amazon Draws Scrutiny For Price Increases. *Forbes*. Retrieved from https://www.forbes.com/sites/tompopomaronis/2017/09/06/hurricane-irma-resulting-in-claims-that-amazon-is-price-gouging-what-we-know/?sh=1d35967e2bd3

Prakash, D., & Spann, M. (2022). Dynamic pricing and reference price effects. *Journal of Business Research*, *152*, 300–314. https://doi.org/10.1016/j.jbusres.2022.07.037

Rao, A. R., & Monroe, K. B. (1989). The Effect of Price, Brand Name, and Store Name on Buyers' Perceptions of Product Quality: An Integrated Review. *Journal of Marketing Research*, *16*(August), 351–357.

Ratneshwar, S., & Mick, D. G. (2013). *Inside Consumption: Consumer Motives, Goals, and Desires*. Hoboken: Taylor and Francis.

Raveendhran, R., & Fast, N. J. (2019). Technology and Social Evaluation: Implications for Individuals and Organizations. In R. N. Landers (Ed.), *The Cambridge Handbook of Technology and Employee Behavior* (pp. 921–943). Cambridge University Press. https://doi.org/10.1017/9781108649636.034

Raveendhran, R., & Fast, N. J. (2021). Humans judge, algorithms nudge: The psychology of behavior tracking acceptance. *Organizational Behavior and Human Decision Processes*, *164*, 11–26. https://doi.org/10.1016/j.obhdp.2021.01.001

Roberts, J. J. (2016). Uber Slammed for Surge Prices After New York City Bombing. *Fortune*. Retrieved from https://fortune.com/2016/09/19/uber-chelsea-bomb/

Rott, P., Strycharz, J., & Alleweldt, F. (2022). Personalised Pricing. Retrieved from https://www.europarl.europa.eu/RegData/etudes/STUD/2022/734008/IPOL_STU(2022)734008_EN.pdf

Seele, P., Dierksmeier, C., Hofstetter, R., & Schultz, M. D. (2019). Mapping the Ethicality of Algorithmic Pricing: A Review of Dynamic and Personalized Pricing. *Journal of Business Ethics*, *65*(5), 2161. https://doi.org/10.1007/s10551-019-04371-w

Seim, K., Vitorino, M. A., & Muir, D. M. (2017). Do consumers value price transparency? *Quantitative Marketing and Economics*, *15*(4), 305–339. https://doi.org/10.1007/s11129-017-9193-x

Spann, M., Fischer, M., & Tellis, G. J. (2015). Skimming or Penetration? Strategic Dynamic Pricing for New Products. *Marketing Science*, *34*(2), 235–249. https://doi.org/10.1287/mksc.2014.0891

Spann, M., Zeithammer, R., Bertini, M., Haruvy, E., Jap, S. D., Koenigsberg, O., Mak, V., Popkowski Leszczyc, P., Skiera, B., & Thomas, M. (2018). Beyond Posted Prices: The Past, Present, and Future of Participative Pricing Mechanisms. *Customer Needs and Solutions*, *5*(1-2), 121–136. https://doi.org/10.1007/s40547-017-0082-y

Thaler, R. H. (1985). Mental Accounting and Consumer Choice. *Marketing Science*, *4*(3), 199–214.

Verboven, F. (2016). Price Discrimination (Empirical Studies). In *The New Palgrave Dictionary of Economics* (pp. 1–5). London: Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_2256-1

Williams, G. Y., & Lim, S. (2024). Psychology of AI: How AI impacts the way people feel, think, and behave. *Current Opinion in Psychology*, *58*, 101835. https://doi.org/10.1016/j.copsyc.2024.101835

Williams, K. R. (2022). The Welfare Effects of Dynamic Pricing: Evidence From Airline Markets. *Econometrica*, *90*(2), 831–858. https://doi.org/10.3982/ECTA16180

Xia, F., Chatterjee, R., & May, J. H. (2019). Using Conditional Restricted Boltzmann Machines to Model Complex Consumer Shopping Patterns. *Marketing Science*, *38*(4), 711–727. https://doi.org/10.1287/mksc.2019.1162

Yalcin, G., Lim, S., Puntoni, S., & van Osselaer, S. M. J. (2022). Thumbs Up or Down: Consumer Reactions to Decisions by Algorithms Versus Humans. *Journal of Marketing Research*, *59*(4), 696–717. https://doi.org/10.1177/00222437211070016

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal of Behavioral Decision Making*, *32*(4), 403–414. https://doi.org/10.1002/bdm.2118

Zafar, F. (2023). 18 Countries with GDPR-like Data Privacy Laws. Retrieved from https://finance.yahoo.com/news/18-countries-gdpr-data-privacy-121428321.html

Zuiderveen Borgesius, F., & Poort, J. (2017). Online Price Discrimination and EU Data Privacy Law. *Journal of Consumer Policy*, *40*(3), 347–366. https://doi.org/10.1007/s10603-017-9354-z