Algorithmic Pricing: Implications for Consumers, Managers, and Regulators

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Abstract

Over the past decade, an increasing number of firms have delegated pricing decisions to algorithms in consumer markets such as travel, entertainment, and retail; business markets such as digital advertising; and platform markets such as ride-sharing. This trend, driven primarily by the increased availability of digital data and developments in information technology, has economic and social consequences that are not yet well understood. The aim of this paper is therefore to examine various implications and challenges of algorithmic pricing for consumers, managers, and regulators. We contribute to the literature by defining and classifying algorithmic pricing, understanding managers' perceptions and adding empirical evidence on its use, raising important considerations for the three stakeholders, and finally outlining research priorities in this area.

Keywords: algorithmic pricing, pricing, programmatic pricing, managerial decision-making, consumer choice

1. Introduction

Over the past decade, an increasing number of firms have delegated pricing decisions to algorithms in consumer markets such as travel, entertainment, and retail; business markets such as digital advertising; and platform markets such as ride-sharing.[1] This trend, driven primarily by the greater availability of digital data and developments in information technology, has economic and social consequences that are not yet well understood. In addition, there is no consistent and simple definition of algorithmic pricing. Several review articles focus on different aspects of algorithmic pricing or related concepts, such as Seele, Dierksmeier, Hofstetter, and Schultz (2019) on ethical considerations, Calvano, Calzolari, Denicolò, and Pastorello (2019) on competition-related issues, and Kopalle, Pauwels, Akella, and Gangwar (2023) on dynamic pricing. However, a comprehensive discussion of different aspects of algorithmic pricing for different stakeholders in the market is missing. Therefore, the aim of this paper is to study the challenges and implications of algorithmic pricing. We define and classify algorithmic pricing, provide empirical evidence on managers' perceptions and use of algorithmic pricing, discuss important aspects of algorithmic pricing for consumers, managers, and regulators, and outline related research priorities.

Key issues related to consumers are their perceptions of and reactions to pricing algorithms. For example, consumers are concerned about the fairness of algorithmic prices, potential price discrimination, and (lack of) transparency in how prices are determined. In addition, consumers may be concerned about the data used to inform algorithms, which may violate their privacy.

A significant challenge for managers is to delegate decision-making authority to a technical function, such as an algorithm, when the decisions directly impact firms and markets. This

[1] A recent example is the announcement and controversy surrounding the use of dynamic pricing at Wendy's. See: https://www.inc.com/bruce-crumley/dynamic-pricing-keeps-spreading-despite-protest-from-wendys-customers.html

challenge is reminiscent of Little's "decision calculus" issues concerning the adoption of decision technology, stemming from managers' uncertainty about the benefits and drawbacks of new technology due to a limited understanding of the system (Little, 1970). For example, managers may wonder whether they are at risk of being caught in a prisoner's dilemma regarding their own and their competitors' pricing decisions. Therefore, firms need guidance on how to make the best use of pricing algorithms by understanding their competitive effects, pricing managers' reactions, consumer reactions, and the impact on business operations throughout the supply chain.

Regulators are concerned about the impact of pricing algorithms on competition, market structure, and market dominance: How do pricing algorithms affect barriers to entry in digital markets? Is there a link between pricing algorithms and inflation? Do pricing algorithms result in collusion? If so, who is responsible for the potential collusion of algorithms? Regulators are also concerned with consumer privacy, non-discrimination, and the potential impact of programmatic pricing on consumer welfare. While recent EU legislation, namely the Digital Markets Act and the Digital Services Act, touches upon algorithms and pricing to some extent, the ongoing regulatory debate remains far from settled and could greatly benefit from academic insights.

We contribute to the literature by defining and classifying algorithmic pricing, developing a survey to measure managers' perceptions of algorithmic pricing, and providing empirical evidence on the use of algorithmic pricing. We further contribute by discussing important aspects of algorithmic pricing for consumers, managers, and regulators, and outlining research priorities.

The remainder of the paper is organized as follows. In Section 2, we define algorithmic pricing, delineate its key features, and elucidate the distinctions between various algorithmic pricing systems. Section 3 provides examples of the adoption of algorithmic pricing. In Section 4, we present some empirical insights on managers' perceptions of algorithmic pricing and its use in offline retailing. Section 5 discusses consumer perceptions and reactions to algorithmic pricing at different stages of the customer journey. Section 6 discusses the opportunities and challenges for managerial decision-making. In Section 7, we outline regulatory concerns and describe how different countries approach algorithmic pricing from a regulatory standpoint. Section 8 concludes the paper with a discussion of research priorities in this area.

2. What Is Algorithmic Pricing?

We generally define algorithmic pricing as "*the use of programs to automate the setting of prices.*"[2] In algorithmic pricing systems, managers define rules and constraints to achieve specific objectives. Based on these guidelines, the algorithm then automatically sets prices. The algorithm can change prices over time and/or across consumers, resulting in dynamic and/or personalized pricing. Therefore, dynamic pricing represents a form of algorithmic pricing that relies on algorithms to adjust prices based on real-time market conditions.

The key difference between algorithmic pricing and traditional pricing methods lies in the automation aspect. While traditional methods involve manual price setting by managers, algorithmic pricing uses algorithms to set prices based on predefined rules and data analysis. Algorithmic pricing also differs from participative pricing, in which both dynamic price changes and personalized prices can be the result of customer interaction in a participative pricing mechanism such as an auction or negotiation (Spann et al., 2018). Prices based on algorithmic pricing systems are typically neither predetermined nor pre-announced. Key features of algorithmic pricing include the type of managerial input required, the specific data needed for the

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[2] 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., Lu, Yao, Chen, & Grewal, 2021).

algorithm to produce the intended output, and whether the output is limited to prices or also includes additional variables, such as production and inventory planning (see Table 1).

Table 1: Characteristics of algorithmic pricing

Feature	*Feature levels*
Managerial input	Rules, constraints, and objectives
Data requirements	Demand, supply, level of granularity
Output	Price(s) and other variables such as inventory/production planning

Algorithmic pricing systems can be differentiated by the degree of decision delegation to the algorithm, the level of managerial input, the extent to which managers understand the input-output relationship and model, the granularity of prices, and the nature of the algorithm, such as whether it includes an element of randomization. Further, algorithmic pricing systems can be distinguished based on who owns the algorithm and sets the prices: the seller (e.g., Amazon and third-party sellers on Amazon) or a platform (e.g., ride-sharing platforms such as Uber to balance supply and demand). Table 2 summarizes the differences among algorithmic pricing systems.

Table 2: Differences between algorithmic pricing systems

Criteria	*Criteria levels*
Decision delegation	Fully or partially (“human-in-the-loop“)
Level of managerial input	Rules, constraints, and/or objectives
Degree of “black boxyness”	Managers understand input-output and/or model
Granularity of prices	Prices vary across time, space, and individuals
Nature of algorithm	Deterministic or planned randomization
Owner of algorithm	Seller or platform set prices

Note: "Deterministic" in this context means that the same input parameters always produce the same output.

3. Adoption of Algorithmic Pricing

Although time-varying or individualized price discounts have been widely used since scanners were adopted in retail stores, evidence of algorithmic pricing surfaced in the 2010s. Airbnb rolled out an algorithmic tool to help hosts set prices as early as 2013, which was later updated in 2015 (Hill, 2015). In spite of this, Zhang, Mehta, Singh, and Srinivasan (2021) found that only 22.5 percent of Airbnb properties in their sample adopted an Airbnb-recommended pricing algorithm. Moreover, on average, adopters saw their revenues increase by 8.6 percent, even though the prices they set after adopting the pricing algorithm were 5.7 percent lower. Similarly, Chen, Mislove, and Wilson (2016) found that 543 out of 1,641 Amazon merchants of best-selling products likely used algorithmic pricing on Amazon, but it is unclear what algorithm they used. Cohen, Hahn, Hall, Levitt, and Metcalfe (2016) showed that surge pricing on the UberX service – set by the platform's algorithm rather than Uber drivers – helped to match the demand and supply of ride sharing in real time, leading to an overall $6.8 billion gain of consumer surplus in the U.S. for 2015 alone.

More recently, Brown and MacKay (2023) tracked high-frequency price data of OTC allergy drugs among the five largest online retailers, and found that while these retailers update prices at regular intervals, the intervals differed widely across firms. They showed that firms that updated their prices more slowly tended to charge higher prices: prices were approximately 30 percent higher for firms who updated their prices weekly and 10 percent higher for those who updated their prices daily, compared to the firm that updated its prices the most frequently (e.g., multiple times within a day). This is not surprising because updating prices frequently allows a firm to undercut its competitors more frequently. In another study, MacKay, Svartbäck, and Ekholm (2022) showed that, when a restaurant food delivery company uses an algorithm to set delivery fees every 10 minutes, the use of algorithmic pricing helps to smooth demand across periods. On average, the delivery fee set by the algorithm is lower than the previous uniform delivery fee, suggesting that algorithmic pricing has the potential to both improve restaurant efficiency and benefit consumers.

Calder-Wang and Kim (2023) collected information regarding 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 in the ride-sharing and other aforementioned settings, they found that the use of algorithmic pricing allowed building managers to set prices that were more responsive to macro conditions such as boom and bust, as compared to non-adopters in the same market.

4. Empirical Insights on Managers' Perceptions and Use of Algorithmic Pricing

In this section, we present survey results on managers' perceptions of algorithmic pricing and a case study on the use of algorithmic pricing in an offline retail environment.

4.1. Survey

To assess the perception and usage of pricing algorithms, we conducted a survey of pricing managers (see Web Appendix A for the survey questions). 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. Pricing managers were asked to participate in a study on current pricing practices. In addition, the authors shared links to the survey on their LinkedIn accounts.

Eighty-three managers participated in the survey, with 12 observations excluded (10 for incompleteness and two for inconsistencies), leaving 71 responses available for analysis. Over 80 percent (87.3%) of respondents reported being very or extremely familiar with their company's price setting 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%).

Results. Most respondents (67.6%) work for a company that uses pricing algorithms for at least some of the products they sell. Not surprisingly, firms that use pricing algorithms change prices more frequently than those that do not, but about half of the firms that use pricing algorithms still only change prices only every quarter or less frequently (see Table A1, Web Appendix B). Overall, most firms, regardless of whether they use pricing algorithms or not, tend to customize their prices to specific consumers, specific segments, and geographic locations (see Table A1, Web Appendix B). Companies most commonly use their cost data (75.7%) and historical revenue or profit data (73%) as inputs for pricing algorithms. Surprisingly, only 56.82% of companies use information about competitors' prices, and just over half of companies use information about past consumer behavior that is useful for customizing prices to each individual customer. While we would expect those using pricing algorithms to be more likely to customize prices to individual customers, we observe the opposite. One possible reason for this is that the majority of these companies that do not use pricing algorithms operate in the business-to-business market.

See Web Appendix B for additional results, including pricing managers' perceptions of the advantages and disadvantages of pricing algorithms, the types of pricing algorithms used, and the data inputs used for the pricing algorithms.

4.2. Case Study

We received data from Evo, 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). We obtained field data from one of the company's clients, which operates gift and memorabilia stores in zoos, aquariums, and museums. The data cover over 220 different stores throughout the United States and Canada.

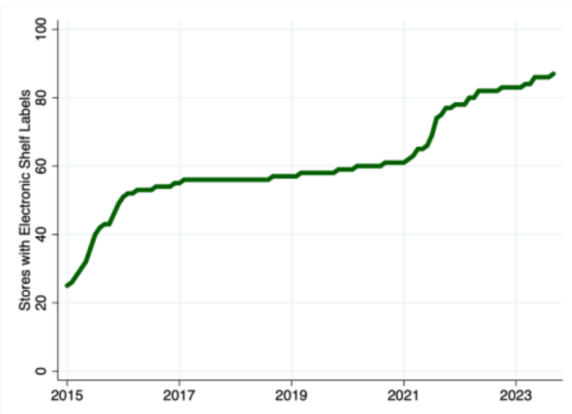
To dynamically set prices in physical stores, the company uses Electronic Shelf Labels (ESLs). ESLs are small *digital screens* that display the price next to each product. See Web Appendix C for a visual representation of the partner company's retail setting. One of the key benefits of ESLs is that they allow companies to implement dynamic pricing (Aparicio & Misra, 2023). In fact, prior to using ESLs, the partner 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, etc.). 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.

While the ESL technology makes it possible to trigger an unlimited number of price changes, managers indicated that keeping a "human in the loop" is critical. For instance, the managers added several constraints to the price optimization process. These included restrictions on overnight price adjustments, limits on price differences between comparable products, boundaries on maximum or minimum prices, considerations for price endings, and rules on the frequency of price changes per week. For example, even if the algorithm suggests $10 for a plush toy raccoon and $90 for a penguin as optimal prices, constraints prevent such extreme price discrepancies.

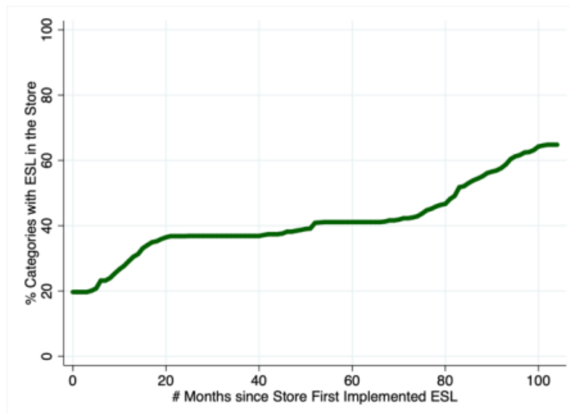
We observe 88 different stores that have adopted ESLs since 2015. Panel (a) of Figure 1 shows the adoption of ESLs across stores over time. Moreover, the rollout of ESLs within a store tends to be gradual. That is, a given store does not suddenly install ESLs on all of its shelves and for all of the products it has in its assortment. Our conversations with managers suggest that stores conduct small experiments to ensure that ESLs work well (and are more profitable) before expanding their use throughout a store. In addition, stores prioritize certain categories or products that tend to sell a sufficient number of units. In fact, Panel (b) of Figure 1 shows that, on average, stores start with ELSs in about 20 percent of its categories. This share increases to 40 percent by the second year and to 60 percent by the seventh year. Again, it is interesting to note that stores do not extend ESLs to every single product or category.

Figure 1: Adoption and rollout of electronic shelf labels (ESL)

(a) Adoption of ESL



(b) Rollout of ESL within the store



Artificial intelligence technology for pricing has allowed stores to achieve two important managerial outcomes: (a) increasing the frequency of price changes and (b) reducing "menu costs" frictions. To show the first result, we estimate the following OLS fixed-effects regression:

$$PriceChange_{i,t} = \alpha + \beta CategoriesESL_{i,t} + \gamma_t + \delta_i + \varphi_c + \varepsilon_{i,t} \qquad (1)$$

where the dependent variable in equation (1), $PriceChange_{i,t}$, represents the percentage of categories in store *i* that underwent a price change in month *t*, multiplied by 100 (so a value of 100 indicates that all categories had a price change, while 0 indicates that none had a price change). The independent variable $CategoriesESL_{i,t}$ denotes the number of categories with ESLs in store i and month t. In addition, γ_t, δ_i, and φ_c stand for month, store, and category fixed effects, respectively. This set of stringent fixed effects implies that the results are not driven by differences across stores or categories.

To show the second result, we estimate the following OLS fixed-effects regression:

$$Products_{i,c,t} = \alpha + \beta ESL_{i,c,t} + \gamma_t + \delta_i + \varphi_c + \varepsilon_{i,t} \qquad (2)$$

where the dependent variable in equation (2), $Products_{i,c,t}$, is the number of products in store i and category c that experienced a price change in month t. The independent variable $ESL_{i,c,t}$ is an indicator variable that takes the value 1 if store i in category c has the ESL system in place in month t. The model is estimated conditional on at least one product having a price change.

The results are shown in Table 3. Column (1) shows that installing an ESL in an additional category increases the probability of a price change by 0.46 percentage points. Thus, the use of ESL increases price variability. Again, intuitively, ESLs allow managers to more easily update prices and run promotions across the assortment. These results are consistent with previous research (Stamatopoulos, Bassamboo, & Moreno, 2021). Finally, column (2) shows that, conditional on a price change, the store updates prices for two fewer products with ESLs, compared to those without ESLs. This reflects that ESLs reduce "menu costs": whereas without ESLs the store used to concurrently implement price changes for many products (on few occasions), ESLs make it easier and less costly to update prices for *fewer* products (Aparicio, Metzman, & Rigobon, 2023). Intuitively, it makes little sense to manually update the price for just one product; instead, the store is likely to wait and update prices for multiple products together.

Table 3: Algorithmic pricing in offline stores with ESLs

	(1) *Price Change*	*(2)* *Products*
ESLs	0.462***	-2.142***
	(0.135)	(0.182)
Constant	32.709***	8.396***
	(0.756)	(0.092)
Observations	79,687	40,587
R-squared	0.256	0.130

Notes: Store, category and calendar month fixed effects included.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

In conclusion, this case study shows, in line with our survey results, that the application of algorithmic pricing in offline retail, facilitated by digital technologies such as ESLs, is only gradually developing, often supported by consulting services. In other words, while ESLs appear to be beneficial for the company, companies may need external support to implement algorithmic pricing. Managers' cautious approach to algorithmic pricing may be explained by uncertainties about customer reactions, fairness concerns, the appropriate decision space, and a volatile regulatory environment. We discuss each of these issues in the following sections.

5. Consumers and Pricing Algorithms

Existing research has explored the impact of algorithmic integration in people's lives, highlighting that algorithms in general can shape the way consumers think and feel about themselves, products, and companies, and how consumers ultimately behave (Yalcin, Lim, Puntoni, & van Osselaer, 2022). At the same time, however, research that relates specifically to pricing algorithms is scant.

In what follows, we aim to shed light on the impact of pricing algorithms at three different stages in the traditional consumer decision-making process: pre-purchase, purchase, and post-purchase. Table 4 provides an overview of how we structure our analysis. Throughout, we provide examples drawn from existing research and real-world scenarios.

Table 4: The impact of pricing algorithms across the consumer decision-making process

	Pre-Purchase	*Purchase*	*Post-Purchase*
Consumer Beliefs and Perceptions	Perceptions of price change, frequency of price change, company/brand, privacy, biases and discrimination, fairness	Price expectations, reference prices, quality inferences, weight placed on price	Price recall, perceptions of price magnitude
Consumer Behaviors	Information search behaviors (e.g., frequency of checking, use of algorithms), strategic behavior (e.g., incognito search)	Brand and product choice, choice deferral and purchase timing, use of price recommendation tools	Continued price checking, repurchasing, customer attrition, loyalty, product returns, complaints
Contextual Factors	Customer characteristics (e.g., experience with algorithmic pricing, segment membership), norms of dynamic pricing in the industry, bases of price discrimination	Customer characteristics (e.g., tolerance for risk and ambiguity, need for cognitive closure), market characteristics (e.g., nature of market competition), urgency of customer need, type of product (e.g., hedonic vs. utilitarian)	Consumer price knowledge, external factors affecting the price obtained (e.g., severity of the circumstances)

5.1. Pre-Purchase Stage

The first stage in a consumer's decision-making journey is the pre-purchase phase. The starting point is thus when consumers recognize that they have a "problem" to solve — they identify a difference between their current state and their ideal state. When this difference is large enough, it triggers action: consumers begin to gather information about relevant features and attributes, and consequently about products or services that can move them closer to the ideal state.

Consumers' beliefs and perceptions about companies that adopt pricing algorithms, or about prices or algorithms themselves, can affect whether they recognize the need to make a purchase or the search process they engage in to find a suitable alternative. First, consumers are likely to hold beliefs about how frequently prices change, and these beliefs could affect whether they start the problem recognition process. For example, consumers may be interested in taking a weekend trip and staying at a hotel, but if the hotel has a high fixed price, consumers may infer that all hotels in the area are unaffordable and postpone the trip or avoid spending the night. Alternatively, if consumers know that prices vary, they may believe that prices may eventually drop and, "just in case," start considering alternatives and monitoring prices, perhaps even with the help of an aggregator or price comparison engine. They may even contemplate making a last-minute decision depending on their assumptions about when prices might be the lowest. All of this, of course, depends on consumers' perceptions of how often and by how much prices change.

Second, consumers may hold certain perceptions regarding firms that use pricing algorithms. They may believe that companies using these tools are simply trying to balance supply and demand, or that companies are trying to exploit a situation to maximize profits (Campbell, 1999; Castelo, Boegershausen, Hildebrand, & Henkel, 2023). Depending on the perceived motive, consumers may decide not to consider a purchase. Consumers may also decide not to consider companies that use pricing algorithms if they believe that these tools leverage private or sensitive data (Victor, Thoppan, Nathan, & Fekete-Farkas, 2018) or may engage in search in "incognito mode" to mask their sensitive information when the process unfolds online. Furthermore, consumers who belong to certain marginalized groups may avoid companies that use pricing algorithms because they believe they will be exposed to biased or discriminatory outcomes (Barocas & Selbst, 2016).

More generally, some consumers may believe that the use of pricing algorithms is unfair (Haws & Bearden, 2006). Perceptions of price fairness can vary with the source of information, so even when observed prices are held constant, perceptions of fairness may differ when formed in a context where pricing algorithms are used (Campbell, 2007).

There are several reasons why consumers may perceive the use of pricing algorithms to be unfair. First, consumers may perceive prices set by pricing algorithms to be unfair if they believe that their use violates the dual entitlement principle (Kahneman, Knetsch, & Thaler, 1986). In general, this principle suggests that customers are entitled to receive a price at or near their reference price, and companies are entitled to earn their reference profit. This suggests that, if a company increases its price to compensate for an increase in costs, consumers may perceive this as fair. However, with dynamic pricing, prices often rise independently of increases in costs (due to fluctuations in demand, inventory levels, market buying patterns, demographics, etc.; Choi, Song, & Jing, 2023), which consumers may then perceive as unfair and decide to stay away.

Second, consumers may perceive prices set by pricing algorithms to be unfair if they believe (or observe) that others pay different amounts (Feinberg, Krishna, & Zhang, 2002; Haws & Bearden, 2006; Kuo, Rice, & Fennell, 2016; Lyn Cox, 2001), or if they believe that algorithms change prices even over short periods of time (Haws & Bearden, 2006). These are both factors that have been shown to lead to perceptions of unfairness. More generally, consumers may also hold perceptions of unfairness toward companies that use pricing algorithms if they perceive that the use of algorithms allows companies to implement price changes more extensively and in ways that have greater impact than when managers make decisions (Duani, Barasch, & Morwitz, 2024).

Beyond beliefs and perceptions, the exposure of consumers to pricing algorithms during the pre-purchase stage can result in differences in their behaviors. For example, the use of pricing algorithms may lead to changes in the frequency or the manner in which consumers search for purchase options (e.g., incognito mode; Lagerlöf, 2023) and for information about prices or other attributes. Pricing algorithms often consider consumers' online search behavior (e.g., the frequency and duration of website visits), consumers therefore may strategically adjust their search behavior based on the (actual or assumed) rules pricing algorithms adhere to. For example, common recommendations for airline ticket shoppers include clearing their browser cookies, booking flights on certain days of the week (e.g., Tuesday), or minimizing repeated flight searches.

Finally, there are contextual factors that can moderate the above-mentioned effects. First, individual characteristics of consumers exposed to pricing algorithms may significantly influence their perceptions and behaviors in the pre-purchase stage. For example, existing work has demonstrated that a consumer's level of product knowledge plays an important role in information processing and search behavior (Alba & Hutchinson, 1987). Knowledgeable consumers are more familiar with product-related experiences (price range, popular brands, etc.) and have greater product-specific expertise (e.g., how to use a product). Because of their existing knowledge, interest, and prior product-related experiences, these consumers can also process product-specific information more efficiently, requiring less cognitive effort and time (W. Johnson & Kieras, 1983).

Interestingly, such a knowledge gap may lead to opposing predictions regarding information search. On the one hand, existing work suggests that, given such low cognitive costs, knowledgeable consumers may be more likely to engage in information search prior to making a purchase decision (E. J. Johnson & Russo, 1984; Punj & Staelin, 1983). On the other hand, novice consumers may seek a greater amount of information due to their limited understanding of the product domain, requiring more time and effort to catch up (Clarkson, Janiszewski, & Cinelli, 2013). It is also possible that the dynamic nature of product prices may be particularly overwhelming for novice consumers, making the information search process seem confusing and complicated.

Second, consumers' prior experiences with algorithmic pricing, even in unrelated consumption contexts, can significantly influence their search behavior and their perceptions of price fairness. For example, a consumer with many prior experiences with dynamic pricing (e.g., hotel bookings, airline tickets) may be more likely to accept the fluctuating nature of prices, and complete the information search process earlier, and view companies deploying such algorithms more favorably (e.g., in terms of fairness).

A third consumer-related characteristic that plays a role in shaping perceptions and search behavior is the group to which consumers belong. Companies are increasingly using algorithms to make price changes automatically and without human intervention. Despite the obvious benefits, such as the adoption of a more consistent and objective process, the effectiveness of algorithms relies heavily on the quality of the data used as input. For example, if the data contain biases against specific consumer groups, the algorithms may inadvertently amplify those biases. Previous research has shown that consumers from certain marginalized groups may be concerned about receiving biased or discriminatory outcomes from algorithms, leading them to avoid companies that use them (Barocas & Selbst, 2016). Accordingly, consumers from minority or marginalized groups may perceive prices as more unfair if they attribute the price changes they encounter to such biases.

Consumers' perceptions and behaviors during the pre-purchase stage can also be shaped by market factors. For instance, fairness perceptions and consumer attitudes toward a company using pricing algorithms can be significantly influenced by market norms regarding 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 the changing nature of prices or price changes more favorably. The same strategy, however, may be perceived differently in markets where frequent price changes are not as common.

Finally, various product- and company-related factors can significantly influence consumers in the pre-purchase stage. For example, fairness perceptions may depend on the actual or assumed criteria that companies use to adjust their prices. Duani et al. (2024) showed that while consumers generally perceive pricing algorithms to be less fair than human price setters, when price discrimination is based on demographics, consumers tend to perceive prices set by algorithms as fairer than prices set by humans. This is because, in the case of demographic price discrimination, consumers feel less judged by algorithms than by humans, and because they view algorithms' decisions as less exploitative and more justified. Also, the transparency of a firm regarding which information the pricing algorithm uses and how prices are set could also affect consumer perceptions and valuations. This transparency could potentially be valued in the same way that price transparency itself is generally appreciated by consumers (Seim, Vitorino, & Muir, 2017).

5.2. Purchase Stage

In the second stage of the decision process, consumers' beliefs and perceptions about price expectations, reference prices, price-quality inferences, and the importance of price relative to other product attributes influence their evaluation of product options and, ultimately, their purchase decisions. Again, we ask how the introduction of pricing algorithms can play a role. First, although it is probably easier for consumers to notice price changes (or patterns in price changes) when simple posted prices are used, they may still form expectations about the changing nature of prices, how often such changes occur, and when prices in general might be at their lowest or highest points (Kannan & Kopalle, 2001) in the context of pricing algorithms. For example, consumers may learn that they can find lower prices for flights if they book in advance or if they depart during the work week and include a Saturday night stay in the trip. They may learn that the price of a ride offered by a car-sharing platform tends to be higher during bad weather and lower in the middle of the day on weekends.

Second, knowing that consumers often perceive utility from the difference between the prices they paid and those they expected to pay (Thaler, 1985), pricing algorithms may cause more variation in these reference prices than fixed pricing (Kannan & Kopalle, 2001). In fact, when companies use pricing algorithms, consumers may hold a distribution of reference prices in their minds rather than a point estimate. This likely complicates the creation of a trusted benchmark and the comparison to the observed price, thus presumably weakening the impact of transaction utility. Alternatively, pricing algorithms may draw more attention to prices, and therefore increase the salience of reference price effects, if the variation in prices is significant (Prakash & Spann, 2022).

For similar reasons, companies that use pricing algorithms may find that consumers draw different 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, consumers may be less willing to draw conclusions about product quality from prices if these vary constantly. The use of price as a signal is muddled by the variation. Moreover, consumers may simply reason that, if product quality is relatively fixed, the fact that prices vary must imply that the two (quality and price) are not necessarily related. Irrespective, consumers may turn to other proxies and indicators to judge quality before making (or not) a purchase. 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).

More generally, in the purchase stage a company's use of pricing algorithms may alter the weights that consumers place on price relative to other relevant product information. On the one hand, pricing algorithms may increase the salience of price, leading consumers to place greater weight on price information and to 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 the variation introduced by pricing algorithms, consumers may de-emphasize price and place instead more weight on other product features.

All of these effects generated by the use of pricing algorithms ultimately lead to concrete differences in consumer behaviors. At a general level, the above discussion as well as the findings from past work on consumer reactions towards algorithms (e.g., Longoni, Bonezzi, & Morewedge, 2019) suggest that the use of pricing algorithms can have significant effects on whether consumers buy, their willingness to pay, which brand(s) they buy, and, in some cases, when, from where, and in what quantities. For example, expectations about the pattern and dynamics of prices enabled by algorithms may influence when consumers decide to buy and the specific composition of that purchase. At the same time, however, consumers may also decide that they need their own technology to counteract the potentially exploitative actions of companies, and as such "recruit" algorithms (e.g., recommendation tools) designed specifically to help them make purchasing decisions.

In turn, these beliefs, perceptions, and behaviors are moderated by contextual factors. One important consumer-related characteristics that can shift how people react to pricing algorithms in the purchase stage is one's tolerance for risk and ambiguity. Prior research has established that consumers with higher levels of risk aversion have lower tolerance for uncertainty and are more willing to pay extra to reduce uncertainty (Simonsohn, 2009; Slovic, 1987). Accordingly, consumers with high levels of risk aversion or low levels of ambiguity tolerance (Budner, 1962) might be more likely to favor products whose prices vary less frequently—for example, more likely to pay an additional fee to "lock in" a price for a flight months before it takes place.

Another relevant individual factor is the level of impulsivity. Impulsivity is a trait associated with limited deliberation before taking an action and an overactive tendency to pursue immediate rewards (Dickman, 1990; Rook & Fisher, 1995). Past work demonstrated that impulsive consumers are more likely to make spontaneous and unplanned purchases (Shiv & Fedorikhin, 1999). They are also less likely to adhere to planned budgets (Lukas & Howard, 2023). In the context of pricing algorithms, it is reasonable to expect such consumers to spend less time conducting thorough evaluation of product options, to act more spontaneously, be more tempted by situational factors such as time-sensitive offers (e.g., Amazon's lightning deals), and be less likely to use decision aids such as recommendation tools.

Third, consumers differ in their need for cognitive closure—people's innate desire for closure and definite option (Kardes, Cronley, Kellaris, & Posavac, 2004). Prior work has demonstrated that need for cognitive closure can plays a central role in the way consumers make decisions and choices (Vermeir, van Kenhove, & Hendrickx, 2002). For example, consumers who have high need for cognitive closure are more likely to terminate their evaluation process and be less sensitive to alternative hypotheses (Kruglanski, Pierro, Mannetti, & Grada, 2006). Accordingly, consumers with an acute need for cognitive closure may react differently to pricing algorithms: they may make decisions quicker and possibly end up paying more.

In terms of market-related characteristics that can influence consumers' beliefs, perceptions and purchasing, one factor is the nature of market competition, which can directly determine the size of the consideration set and whether (or how) the product options can be compared. For example, in situations where there is a single electricity provider in a city, the likelihood of not making a purchase, or leaving the company is considerably reduced. Similarly, in cases where a product is patented (e.g., a medication for a rare disease), depending on the urgency of the need consumers may find themselves compelled to purchase the product, irrespective of how prices are set. Conversely, when a product has several direct alternatives available (e.g., flu vaccine), this allows consumers to engage in evaluation of product options, reflect on how important it is that one or more companies in that market use pricing algorithms, and decide accordingly.

A second market-related factor is whether demand for a product is driven by unforeseen (and often important) external circumstances (e.g., urgent need for tire chains during a severe blizzard, a surge in demand for masks during a pandemic). Here, consumers might be less likely to react to price fluctuations as the urgency of the need tends to outweigh most changes in price.

Finally, consumer responses to dynamic pricing during the purchasing stage can be shaped by various factors related to the product or company itself, including the product's price point (cheap versus expensive) and purchase rate (frequent versus infrequent). For example, certain products are bought frequently and are relatively inexpensive (e.g., toothpaste), whereas others are infrequent and costly (e.g., laptops). When dealing with the latter type, consumers tend to be more involved in the decision-making process and make more careful choices. In such cases, price fluctuations prompted by pricing algorithms can have a more substantial impact. For example, consumers can opt to wait to secure a better deal, or to adopt a price recommendation tool to (supposedly) improve the quality of the decision. Conversely, the fact that a company uses pricing algorithms may not be a telling factor when products are less expensive or are more frequently purchased (e.g., short-distance Uber ride, soda drink). Such decision-making processes, due to the lower risk associated with them, might not require high involvement and consumers might assign less importance to such information when making decisions.

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. Prior research has consistently shown that consumers tend to view products as either hedonic or utilitarian (Ratneshwar & Mick, 2013). While hedonic products are mainly based on 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 affects not only consumers' perceptions of the company and its products (e.g., perceived quality), but also consumers' purchasing evaluations and decisions when these companies adopt pricing algorithms. For example, when luxury brands lower their prices through a dynamic pricing strategy, consumers may view this as a limited opportunity to own a luxury product (e.g., Hermès purse), skip the evaluation stage, and make an impulsive purchasing decision. It is harder to envisage a similar process in the case of mainstream brands (e.g., H&M purse).

5.3. Post-Purchase Stage

Companies' use of pricing algorithms can continue to influence consumers even after they have made a purchase. One example of this is price recall. Past research has shown that consumers' memory for prices, even for products recently purchased, can be quite low (Dickson & Sawyer, 1990), although past prices may still affect consumers even when they cannot consciously recall price (Monroe & Lee, 1999). Price knowledge and price recall may be affected by the variability of prices. An intriguing question is the direction of this effect. It is intuitive to think that frequent price changes make recall more challenging and reduce accuracy. Yet, the fact that consumers may focus more on prices because they vary may actually increase recall — though price knowledge may well be stored as a distribution rather than a point estimate.

The use of pricing algorithms may also affect perceptions of the magnitude of offered prices. If consumers view prices more as a distribution rather than a fixed point, it is unclear which aspects of that distribution will impact their perceptions of price magnitude. Additionally, it remains uncertain whether they will perceive the offered prices as high or low. Of course, consumers may use only the price they received to form a price magnitude perception. Alternatively, consumers may use a summary statistic from the distribution such as the mean, median, or mode of past observed prices. Yet another alternative is that these perceptions are driven more by the extremes observed in the distribution, including the lowest or highest prices. Finally, consumers' price magnitude perceptions might be affected by the variance of observed prices: it is possible that price magnitude perceptions are more tempered and held with less confidence when prices are more variable.

Importantly, the above effects matter because they may ultimately lead to behaviors that impact consumers' satisfaction with their purchases and the companies from which they purchased. For example, it is not unreasonable to expect that consumers who know that prices vary over time will return to the websites or stores where they made a purchase and check whether they would have gotten a better or worse deal if they had waited. This ongoing price checking may also lead to regret or elation, depending on the outcome (Pizzutti, Gonçalves, & Ferreira, 2022). Regardless, it is likely to create some stress due to the lack of closure and price certainty. Such (dis)satisfaction is expected to influence other important post-purchase behaviors, including product returns or repeat purchases (i.e., customer retention), word of mouth, and referrals or complaints (on social media, etc.).

Finally, as seen already in the previous two stages of decision-making, these belief, perceptions, and behaviors are likely moderated by a variety of contextual factors. As mentioned, consumer satisfaction and the tendency to voice complaints is closely linked to one's ability to move on following a purchase decision. At the moment of payment, the decision process of evaluating and choosing among options is complete (Hsee, Loewenstein, Blount, & Bazerman, 1999). Some consumers, however, can continue to ponder what their situation would be like had they made a different choice, and experience post-choice regret (Zeelenberg, 1999). This tendency varies among people. Consumers with such persistent contemplation can find it particularly challenging to move on and experience closure when pricing algorithms are employed, as frequent price fluctuations can occur within days, hours, or even minutes. Consequently, consumers who struggle to find closure can be less satisfied, less likely to purchase from the same company in the future or more likely to return products.

Second, consumers' post-purchase behaviors are also likely affected by the urgency of their needs (e.g., a medical emergency) and severity of the circumstances (e.g., a natural disaster). In such cases, consumers are unlikely to be sensitive to the decisions of pricing algorithms when it comes to making a purchase, but brand image and future interactions are at jeopardy. For example, a popular ride-share company, Uber adopts surge pricing strategy, and has profited from many natural disasters (e.g., flooding), extreme weather events (e.g., hurricane) or other crises (e.g., hostage siege) through their surge pricing. During Hurricane Sandy in 2012, Uber fares surged to two or three times their regular fares, drawing substantial criticism for capitalizing on dire circumstances. This led to a tarnished brand image and resulted in many consumers vowing never to use Uber again. To fix their reputation, Uber agreed to cap their surge pricing during extreme events and donated money to related charitable causes, however, the damage was already done, and many consumers remained resolute in their decision.

6. Managers and Pricing Algorithms

Recent developments in algorithmic pricing have created new business opportunities, with its adoption being amplified by ongoing discussions among executives, consultants, and journalists about the vast potential of artificial intelligence (AI) and tools incorporating it to support and perhaps even replace managerial decision-making. The result has been a perfect storm for managers, who are inundated with constant buzz about this new "supernatural" tool, while at the same time having to make decisions about its use. Most managers have only a partial understanding of its capabilities and limitations and face a classic managerial dilemma. As with any new technology, managers do not thoroughly understand the algorithms and thus are uncertain about their ability to deliver. Should they allow this new technological tool to take over decision-making in their organizations? If they decide to use algorithms, when should they use them and in what capacities? What are the strategic and competitive implications of algorithmic pricing? The challenge is delicate, as pricing decisions directly affect their businesses, consumers, competitors, and relevant markets. To navigate this complexity, managers must seek a balance between leveraging AI for efficiency and maintaining oversight to ensure alignment with strategic objectives.

The potential benefits of pricing algorithms are clear. Among them are simplifying managers' price decision tasks and empowering managers to adopt more efficient price-setting procedures. They can allow managers and firms to respond more quickly to changes in markets, especially changes in supply and demand, thereby increasing profits (Ham, He, & Zhang, 2022; J. P. Johnson, Rhodes, & Wildenbeest, 2023). In addition, prices can be tailored to fine-grained customer segments, even to individual customers in real-time through automated processes. The algorithms can analyze changes in costs, capabilities, and capacities, translating these into changes in supply. They can also assess shifts in consumer behavior and competitive decisions, translating these into changes in demand. Another potential benefit is reducing or even eliminating the human biases that impair managers' decisions. For example, an algorithm can be designed to avoid the typically pitfalls in human decisions, such as being influenced by sunk costs, driven by regret and loss aversion, and being subject to reference effect and path dependence etc. However, adoption of pricing algorithms will be a slow process because machine learning algorithms require significant amounts of past data to accurately predict customer behavior and competitors' reactions, as well as to identify and eliminate previous biased processes.

When carefully tailored, such algorithms should allow for improved coordination between firms and managers by aligning their incentives effectively. But the process is not straightforward. The current generation of algorithms has not been able to do so successfully and/or has not incorporated the various incentives effectively (Bertini & Koenigsberg, 2021).

Another potential benefit relates to competition. Can algorithms be designed to mitigate the negative effects of price competition? Perhaps, but their use raises other potential risks. Will the use of such algorithms lock firms in prisoner dilemmas? Will they allow firms to collude? If so, how will regulators react? Who assumes responsibility for the decisions and for regulating the firms? Also, what do price changes signal? Prices send strong messages, and the overarching message a competitor (or its algorithms) may infer will affect the effectiveness of the algorithm.

It is worth pointing out that, while practices and studies on algorithmic pricing have largely demonstrated its short-term effectiveness, research on the long-term and strategic implications of pricing algorithms is particularly lacking. One long-term and strategic aspect of algorithmic pricing is its impact on competition. A few recent studies have suggested the potential collusive behaviors resulted from the use of similar algorithms by competing firms (Assad, Clark, Ershov, & Xu, 2024; Brown & MacKay, 2023; Calvano, Calzolari, Denicolò, & Pastorello, 2020; Hansen, Misra, & Pai, 2021; Miklós-Thal & Tucker, 2019). Yet it is not conclusive whether this is true across different industries, with the proliferation of the algorithms and the advancements in the methodologies used in the algorithms (see Section 7.1 for a deeper discussion of algorithmic collusion). How could firms avoid collusion, e.g., should the algorithms be changed to incorporate a component to prevent collusion? Or should firms differentiate themselves in terms of the algorithms used in addition to product differentiation? Many interesting and important questions remain to be answered.

Another important strategic aspect of algorithmic pricing, which has received even less attention, is its impact on perceived product/service quality and brand equity. A feature often associated with algorithmic pricing is the increased frequency of price changes. Previous research has showed that frequent price promotion may negatively affect perceived brand equity (Erdem, Keane, & Sun, 2008). Will this be applicable to the frequent price changes made by pricing algorithms? If so, how might firms balance the short-term gain in revenue with the long-term loss of brand equity and what would be implications of product quality decisions?

A commonly held belief in pricing is that high price may signal high quality (Rao & Monroe, 1989) and the underlying mechanism that rationalize it is that customers may infer that only a high-quality firm may charge a high price and it is not optimal for a low-quality firm to mimic it due to customer heterogeneities and future selling opportunities (Milgrom & Roberts, 1986). Yet an important assumption that makes such rationalization of price signaling possible is that the same price is charged to different customers. The arrival of algorithmic pricing, however, has made differential pricing on customers possible with almost negligible cost. In fact, being able to customize prices to different customers is considered as a main benefit of algorithmic pricing. Then a question naturally arises: Would the rationality of price-quality signaling still hold in the era of algorithmic pricing? As discussed in Section 5.2, algorithmic pricing may change consumers' quality inferences from prices, and thus require changes in brand equity and quality decisions. Interestingly, the call for responsible and unbiased AI requires firms to not price discriminate on some protected demographic variables, such as race and gender. Would such restrictions actually help restore the capability of quality signaling by pricing algorithms? Again, there are many interesting and important issues to explore here.

Additional potential challenges that can reduce the benefits of using algorithms include the processes by which firms implement new procedures. How can managers ensure that new tools will be adopted for all relevant firm functions and how can managers be convinced to accept the tools and be trained to use them? The solution would depend on how pricing decisions are made within the firms. Ideally, firms should take the adoption of pricing algorithms as an opportunity to streamline the pricing decision-making within the organization and improve the coordination of different functional units. Given the potential risks of data privacy, AI biases, and antitrust concerns associated with algorithmic pricing, an oversight committee at the firm-level may be recommended.

Further challenges arise from managers' aversion to adopting algorithms, mirroring the resistance often observed among consumers (see also Section 5.1). Previous studies indicate that humans might not opt for algorithms over human decision-making, even when algorithms consistently outperform humans (Dietvorst, Simmons, & Massey, 2015). This aversion towards algorithms can be due to a variety of reasons, including the opaqueness in AI process (Yeomans, Shah, Mullainathan, & Kleinberg, 2019), desire for some control and modification over imperfect algorithms (Dietvorst, Simmons, & Massey, 2018), among others. Managers are also likely to be concerned about the ramifications adoption will have for their roles. These kinds of concerns can engender aversion and resistance among managers when weighing adoption of algorithms. Such concerns may be addressed with a three-pronged approach. First, managers need to be trained and informed about how the algorithm works. The development of explainable AI that demystifies the black-box nature of the machine learning algorithms would be helpful on this front. Second, managers' insights might be incorporated into the algorithm. This can be especially valuable when past data are limited. Yet caution should be exercised to avoid bringing any human biases into the algorithm. Third, and perhaps most importantly, managers should be invited and actively engage in overseeing the algorithms to mitigate the potential risks of using it. Managers should be encouraged to interact with customers and gather feedback about their reactions to and concerns regarding pricing algorithms, which might not be observable or inferable from revealed customer behavior. Depending on the nature of the uncovered consumer concerns, managers may need to make adjustments to the algorithms.

Relatedly, many two-sided platforms adopt pricing algorithms with the rationale of assisting sellers who often lack managerial capabilities. The efficacy of such algorithms hinges not only on their performance but also on seller adoption and usage. Seller skepticism, rooted in a general aversion towards algorithms, presents a barrier. An additional challenge in the successful deployment of the pricing algorithms in platforms is that it may be unclear to sellers whether the algorithm is maximizing the platform's or seller's revenue. One reason for this is because platforms do not have accurate information about sellers' marginal costs, and therefore, platforms earn a fixed share of sellers' revenue, not profit. This provides an incentive for platforms to adopt algorithms that set sellers'-revenue-maximizing prices instead of sellers'-profit-maximizing prices. Therefore, while the platform has an incentive to aid sellers' pricing decisions, its objectives may not necessarily align with those of the sellers. If the platform's algorithm maximizes the platform's revenue, what would be its long-term implication on sellers' adoption of the pricing technology and on the platform's long-term revenue? What could be possible solutions for aligning the incentives of the involved parties? These are all interesting areas to explore in the future.

Finally, using algorithms to make price decisions requires coordination with managers responsible for marketing and operational inputs such as the level of quality built into products and services, quantities held in inventory, promotion efforts, and channel designs. Some of those decisions, such as inventory levels and promotions, are frequent ones. Most likely, and ideally, those decisions should also be automated with algorithms. Therefore, an integrated algorithm that jointly optimizes pricing, promotion, inventory, and customer service would be desirable. And input from different functional units that are responsible for these aspects would be critical for the success of such an algorithm. The other decisions, such as product quality and channel design, tend to be more strategic and long-term. While it might require some time to fully understand the strategic and long-term impacts of pricing algorithms due to data availability, as algorithmic pricing is still at its nascent stage, explorations and insights from academic research could be especially valuable on this regard.

7. Regulators and Pricing Algorithms

Although the utilization of algorithmic pricing has been limited until recent years, it has sparked regulatory concerns in various areas. Antitrust authorities have expressed several concerns related to competition, including concerns regarding horizontal price-fixing (i.e., explicit or tacit price collusion among competitors) and vertical price-fixing (e.g., resale price maintenance). Consumer protection agencies are concerned that algorithmic pricing may lead to excessive prices, price gouging, or undesirable price discrimination. Below we discuss major regulatory concerns, and then describe how policymakers around the globe have attempted to regulate algorithmic pricing.

7.1. Main Regulatory Concerns

While, as illustrated in Section 3 above, algorithmic pricing can present advantages for both consumers and adopting firms, concerns have been raised about its potential to foster collusive pricing and unfair price discrimination practices. More recently, researchers have also pointed to the possibility of price bubbles forming due to the interaction between users and algorithms.

Collusion. According to classical game theories, collusive pricing is inherently unstable because every cartel member has an incentive to secretly deviate and thus the success of explicit collusion depends on how the cartel can effectively detect and punish deviators. Tacit collusion follows the same logic: even if the colluding firms do not communicate with each other explicitly, the extent to which the collusive price is sustainable depends on each member firm's perception of how other member firms may dynamically react to its deviation in price.

Calvano et al. (2020) studied the potential impact of algorithmic pricing on collusion by simulation. 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 found that the algorithms consistently learned to charge supracompetitive prices, without communicating with one another. Consistent with theory, the high prices were sustained by collusive strategies with a finite phase of punishment followed by a gradual return to cooperation. Similarly, after finding heterogeneity in the pricing technology used and frequency of price updating for OTC allergy drugs, Brown and MacKay (2023) modeled a competitive (Markov perfect) equilibrium. They found that the introduction of simple pricing algorithms can increase price levels, generate price dispersion, and exacerbate the price effects of mergers. Using simulation, Asker, Fershtman, and Pakes (2022) further showed that whether price increases are above competitive levels depends on the level of sophistication of the algorithm. More recently, Fish, Gonczarowski, and Shorrer (2024) use Open AI's GPT-4 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). Above all, 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.

Empirically, Assad et al. (2024) studied the impact of algorithmic pricing in Germany's retail gasoline market. The algorithmic pricing software was available since 2017, and gas stations' algorithmic pricing adoption was inferred from structural changes in their pricing patterns. After using instrumental variables to control for the potential endogeneity of the adoption decision, Assad et al. (2024) found that pricing algorithm adoption increases the profit margin in duopoly and triopoly markets, but only if all stations adopt the algorithm.

As cited above, Calder-Wang and Kim (2023) studied the use of algorithmic pricing by property management companies. They found that markets with greater algorithmic pricing penetration experienced higher rents and lower occupancy in the period after the 2007-2008 financial crisis, which is consistent with either price coordination through the algorithm or widespread pricing errors among non-adopters. They further estimated a structural model of rent demand in the Seattle market and then performed a battery of conduct tests. They found that a model of property managers' own-profit-maximization is favored over a model of full coordination regardless of non-adopter sophistication.

Unfair pricing. Dynamic pricing, a mechanism that relies on algorithms to adjust prices based on real-time market conditions, can lead to prices that are perceived as unfair by consumers when they become excessive (e.g., price gouging) or discriminatory. For example, during unusual events that disrupt markets, such as floods (Crane, 2023) and 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 include the high observed prices of flights and water sold through online markets before an approaching hurricane (Popomaronis, 2017). Although some firms occasionally 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, their effectiveness can vary, and concerns persist.

Dynamic pricing can also serve as a tool of price discrimination. As shown by Williams (2022), dynamic airline pricing benefits early-arriving, leisure consumers at the expense of late-arriving, business travelers. When aggregated over markets, welfare is higher under dynamic pricing than under uniform pricing. The direction of the welfare effect at the market level depends on whether dynamic price adjustments are mainly driven by demand shocks or by changes in the overall demand elasticity. 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).

Algorithmic price discrimination can arise not only from dynamic pricing but also from personalized pricing. Using two randomized field experiments on ZipRecruiter, Dubé and Misra (2023) found 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 found that consumer welfare may even increase with personalized pricing. In short, consistent with the classical theory, these studies suggest that any algorithm regulation concerning price discrimination needs to articulate how policy makers make tradeoffs between the welfare of different types of consumers.

Price bubbles. When market players rely on the same algorithms to determine market prices, the algorithm has a potential to propagate errors throughout the whole market, even if the market includes many players and no one has substantial market power. This could create long-lasting price bubbles, akin to how a content recommendation algorithm on a social media website may create an echo chamber among individual platform users.

Fu, Jin, and Liu (2022) studied this possibility in the context of Zillow, where both home buyers and sellers were shown to rely on Zestimate (Zillow's algorithmic estimate of current house value) in their listing and purchase decisions. Further, the estimates from Zestimate were shown to incorporate such human behavior almost immediately after listing and sold prices become publicly available. However, their simulation suggested that random disturbances in the Zestimate algorithm are short-lived and eventually diminish, mainly because all marginal effects across stages of the selling process—though sizable and significant—are less than one. They further validated this insight in the real data by leveraging the COVID-19 pandemic as a natural experiment. They found consistent evidence that the initial disturbances created by the March-2020 declaration of a national emergency faded away in a few months, which alleviates the concern that the feedback loop between human behavior and the Zestimate algorithm generates persistent error propagation.

7.2. Regulatory Actions in Different Countries

Despite the concerns highlighted above, most countries, to date, have adopted relatively conservative positions to address the antitrust or consumer protection concerns related to algorithmic pricing. In the United States, many experts argue that the current legal framework is sufficient to assess pricing algorithms and their impact on competition and consumers. For example, the Sherman Act's Section 1 can impose criminal penalties for explicit collusion. For instance, in 2015, the Department of Justice (DOJ) made its first prosecution targeting internet commerce and pricing algorithms using existing regulations. In the case of United States vs. Topkins, two executives and a commercial retailer were successfully prosecuted for using pricing algorithms to coordinate their wall posters' prices on the Amazon Marketplace. They employed agreed-upon algorithms to avoid price competition among themselves, leading to increased online poster prices. These defendants plead guilty to a Section 1 violation. As another example, more recently 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.

Addressing tacit collusion poses a greater challenge, and, at present, the Federal Trade Commission's (FTC) authority under 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. Ezrachi and Stucke (2017), among others, have suggested expanding antitrust laws to encompass tacit collusion.

MacKay and Weinstein (2021) argue that even without (explicit or tacit) collusion, algorithmic pricing can result in increased prices for consumers in competitive markets. They focus on a type of conduct called non-collusive algorithmic pricing in which supra-competitive prices can be supported even when some firms are charging a lower price than others. MacKay and Weinstein (2021) discuss how regulators can consider addressing this type of conduct with price caps, or by limiting features of the price setting algorithms themselves, such as when they set prices or how often they can set prices.

Regarding algorithmic price discrimination and dynamic pricing, regulators typically refrain from intervening unless it is accompanied by anticompetitive, unfair, or deceptive practices. The U.S. maintains that personalized pricing alone, without negatively affecting market function, may even enhance overall welfare (United States, 2018).[3] Further, several state price gouging laws regulate price spikes by limiting price increases for critical goods and services like gasoline during emergencies.[4]

Anticompetitive effects of price discrimination (e.g., predatory pricing) can be addressed using the Sherman Antitrust Act and subsequent legislation (such as the Robinson-Patman Act of 1936).[5] However, concerns arise that the current regulatory landscape may be insufficient to protect competition in cases where the ability to employ personalized pricing is vital for sustaining a business. In such instances, smaller companies lacking the resources to implement price discrimination strategies may be forced out of the market, thereby reducing overall market competition.[6]

Sensitive data that could potentially be used for personalized pricing is protected by various federal and state laws. The Equal Credit Opportunity Act (ECOA), enforced by the FTC, is an example of such legislation, prohibiting credit discrimination based on race, color, religion, national origin, sex, marital status, age, or the receipt of public assistance. Regulators claim to have adapted to the expanding artificial intelligence industry by employing new enforcement tools.

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[3]While price discrimination is often seen by economists as improving market efficiency (especially as one approaches first-degree price discrimination) some scholars argue that price discrimination is harmful for consumers and that firms' improved accuracy in predicting consumers' willingness to pay has the potential to further harm consumers by reducing the benefits (consumer surplus) that consumers derive from transactions (Woodcock, 2019).

[4]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 (Williams, 2022).

[5]See Lina M. Khan, Amazon's Antitrust Paradox, 126 YALE L.J. 710, 768-770 (2017) (describing how Amazon used its "pricing bots" to strategically undercut prices its rival Quidsi charged for diapers and other baby products, ultimately resulting in Quidsi being forced to sell itself to Amazon).

[6]See https://www.pulj.org/the-roundtable/price-discrimination-good-for-companies-good-for-consumers

For example, since 2019, "algorithmic disgorgement" has been employed as a penalty against companies using illegally obtained data (e.g., children's location data without parental consent). This penalty mandates that firms delete machine learning models and algorithms developed with improperly obtained data.[7]

However, even if an algorithm is not built using specific protected customer characteristics such as race, discrimination based on these characteristics may still persist. This is because there might be correlations between a person's protected attributes and their behaviors or other features captured in the data, which can lead to biased outcomes (Ascarza & Israeli, 2022).

In Europe, both the European Union (European Union, 2017) and the United Kingdom (United Kingdom, 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 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.[8]

Despite this perspective, these countries have recently taken legislative steps which have implications for algorithmic pricing. The European Union has recently put into effect the Digital Markets Act (DMA) and the Digital Services Act (DSA), collectively known as the Digital Services Package.[9] These regulations primarily aim to create a secure online environment, protect

[7]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
[8]See https://ec.europa.eu/competition/antitrust/cases/dec_docs/40465/40465_337_3.pdf
[9]The Digital Services Package was officially proposed by the European Commission in December 2020. The DMA entered into force on November 1, 2022 and became applicable, for the most part, on May 2, 2023. On August 25, 2023, the Digital Services Act came into effect for very large online platforms and very large online search engines. It became fully applicable to other entities on February 17, 2024.

user rights, and promote fair competition. The DSA introduces transparency requirements for online platform providers utilizing recommender systems. Under the DSA, these platforms are obliged to clearly outline in their terms and conditions the main parameters used in their recommender systems. They must also provide recipients of their service with options to modify or influence these parameters in a straightforward manner. This offers consumers more information about the algorithmic mechanism behind the recommender system, and it allows them to select and modify their preferred options at any time. While the apparent focus of these regulations pertains the use of recommender systems, they have implications for algorithmic pricing. Under such regulations, companies may face restrictions on their ability to use personal characteristics to offer different prices to users for the same products or services. Additionally, users may have the option to opt out of algorithms that influence pricing decisions. As a result, companies using algorithmic pricing may need to adapt their strategies and algorithms to comply with these regulations.

In the case of the DMA, two noteworthy provisions stand out. First, it compels gatekeepers to provide annual updates on their consumer profiling techniques to the European Commission, thus enhancing transparency in profiling practices. Secondly, the DMA emphasizes the need for gatekeepers to enforce transparent, fair, and non-discriminatory conditions in their activities. While the focus here seems to be on preventing gatekeepers from favoring themselves on their core platform services through ranking and related practices, this too may have implications for algorithmic pricing.

In addition to the Digital Services Package, the EU Omnibus Directive, implementing the EU's "New Deal for Consumers" and passed in 2020, imposed new obligations on companies involved in personalized pricing, including the requirement to inform consumers in a clear and understandable manner whenever the online price they encounter is determined through automation based on their individual consumer behavior. In April 2023, the UK introduced its draft Digital Markets, Competition, and Consumers Bill, which aligns with EU regulations to establish a pro-competitive framework for digital markets, and is expected to enter into force in 2024.

While current competition laws are generally seen as adequate for evaluating pricing algorithms, concerns about monitoring and enforcement have been raised. Regulators in the United States and several European countries have expressed concerns about the efficacy of traditional guideposts for detecting modern anticompetitive behavior and highlight the importance for continuous regulatory vigilance in response to the increased sophistication of the algorithmic pricing strategies used by companies (Mekki, 2022; Montjoye, Schweitzer, & Crémer, 2019).

China has played a pioneering role in regulating algorithms. In March 2022, the Internet Information Service Algorithmic Recommendation Management Provisions took effect, which is part of a three-year plan initiated by China's cyberspace watchdog in September 2021. While initially driven by concerns about algorithms' role in disseminating online information, these regulations have also been used in various contexts involving algorithms. They specifically prohibit price discrimination driven by algorithms and grant users the ability to opt out of algorithmic recommendations.

8. Conclusion and Research Priorities

In this paper, we define algorithmic pricing and distinguish it from other concepts that lead to dynamic prices, such as participative pricing. We explore the issues and challenges associated with implementing algorithmic pricing for the key stakeholders in a market: consumers, managers, and regulators. We highlight the managerial challenges by presenting empirical evidence from a survey of pricing strategy practitioners. Additionally, a case study sheds light on the implementation and use of algorithmic pricing in offline retailing. We conclude that as algorithmic pricing continues to gain traction in both online and offline markets driven by digital transformation, several key challenges remain unresolved. We summarize the key research priorities related to these challenges in Table **5**.

We identify the following research priorities regarding consumers and algorithmic pricing: (i) consumer perceptions of algorithmic pricing and how these perceptions change with increasing use of algorithmic pricing; (ii) the impact of transparency regarding the use and specific features of pricing algorithms on consumer perceptions of algorithmic pricing; (iii) the impact of algorithmic pricing on consumers' quality inferences from prices in different product categories; (iv) the impact of algorithmic pricing on reference price and price sensitivity, and (v) brand loyalty.

With respect to firms and managers, we recommend future research to (vi) examine the antecedents and moderators of managers' potential aversion to pricing algorithms that inhibit their use; (vii) investigate the optimal level and type of managerial input and its implications for data requirements; and (viii) quantify the effectiveness of algorithmic pricing in different industries, geographic locations, and online versus offline markets. In terms of regulatory tensions, it is important to (ix) learn whether firms need to adopt institutional and technical measures to avoid discriminatory and anti-competitive 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.

From a regulatory perspective, future studies are needed to (x) understand the longer-term effects of pricing algorithms on competition, price levels, price dispersion, and firm profitability; (xi) assess the impact of emerging regulations (e.g., regulations in the EU, the US and China) on the adoption and performance of pricing algorithms; and (xii) explore potential trade-offs between data requirements for the efficient use of pricing algorithms and privacy or other data regulations.

Table 5: Key research priorities for algorithmic pricing

Research priority	***Examples***
Area: Consumers	
Transparency and perceptions	How does transparency about algorithmic pricing affect consumers' (fairness) perceptions of pricing algorithms?
Price-quality relationships	How does algorithmic pricing change consumers' quality inferences from prices (for different product categories)?
Reference price effects and price sensitivity	How does algorithmic pricing affect reference price formation and price sensitivity?
Brand loyalty	Does algorithmic pricing affect consumers' brand loyalty?
Area: Managers	
Algorithmic Aversion	Antecedents and moderators of managers aversion towards algorithms that inhibit their use
Input to pricing algorithms	(Optimal) level and type of managerial input and data requirements
Effectiveness of algorithmic pricing	Studying the effectiveness of algorithmic pricing across industries, geographic locations, and online vs. offline markets
Organizational governance and (internal) oversight	Should firms establish institutional and technical policies to avoid discriminatory and anti-competitive outcomes of algorithmic pricing?
Area: Regulators	
Competition	Longer-term impact of pricing algorithms on competition, price levels, price dispersion and firm's profitability
Regulatory impact	Assess the impact of emerging regulations (e.g., EU DMA and AI Act; regulation in the U.S. and China) on conduct and performance of pricing algorithms
Data requirements and privacy regulation	Study the trade-off between data requirements for efficient use of pricing algorithms and privacy regulation

References

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. *Journal of Consumer Research*, *13*(4), 411–454.

Aparicio, D., Metzman, Z., & Rigobon, R. (2023). The pricing strategies of online grocery retailers. *Quantitative Marketing and Economics.* Advance online publication. https://doi.org/10.1007/s11129-023-09273-w

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

Asker, J., Fershtman, C., & Pakes, A. (2022). Artificial Intelligence, Algorithm Design, and Pricing. *AEA Papers and Proceedings*, *112*, 452–456. https://doi.org/10.1257/pandp.20221059

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

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

Budner, S. (1962). Intolerance of ambiguity as a personality variable. *Journal of Personality*, *30*, 29–50. https://doi.org/10.1111/j.1467-6494.1962.tb02303.x

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. (1999). Perceptions of Price Unfairness: Antecedents and Consequences. *Journal of Marketing Research*, *36*(2), 187–199. https://doi.org/10.1177/002224379903600204

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

Castelo, N., Boegershausen, J., Hildebrand, C., & Henkel, A. P. (2023). Understanding and Improving Consumer Reactions to Service Bots. *Journal of Consumer Research*, *50*(4), 848–863. https://doi.org/10.1093/jcr/ucad023

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

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

Clarkson, J. J., Janiszewski, C., & Cinelli, M. D. (2013). The Desire for Consumption Knowledge. *Journal of Consumer Research*, *39*(6), 1313–1329. https://doi.org/10.1086/668535

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

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/

Dickman, S. J. (1990). Functional and dysfunctional impulsivity: Personality and cognitive correlates. *Journal of Personality and Social Psychology*, *58*(1), 95–102. https://doi.org/10.1037/0022-3514.58.1.95

Dickson, P. R., & Sawyer, A. G. (1990). The Price Knowledge and Search of Supermarket Shoppers. *Journal of Marketing*, *54*(3), 42–53.

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

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

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. (2017). Artificial Intelligence & Collusion: When Computers Inhibit Competition. *University of Illinois Law Review.* Advance online publication. https://doi.org/10.2139/ssrn.2591874

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

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

Ham, S. H., He, C., & Zhang, D. (2022). The promise and peril of dynamic targeted pricing. *International Journal of Research in Marketing*, *39*(4), 1150–1165. https://doi.org/10.1016/j.ijresmar.2022.01.005

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

Hsee, C. K., Loewenstein, G. F., Blount, S., & Bazerman, M. H. (1999). Preference reversals between joint and separate evaluations of options: A review and theoretical analysis. *Psychological Bulletin*, *125*(5), 576–590. https://doi.org/10.1037/0033-2909.125.5.576

Johnson, E. J., & Russo, J. E. (1984). Product Familiarity and Learning New Information. *Journal of Consumer Research*, *11*(1), 542. https://doi.org/10.1086/208990

Johnson, J. P., Rhodes, A., & Wildenbeest, M. (2023). Platform Design When Sellers Use Pricing Algorithms. *Econometrica*, *91*(5), 1841–1879. https://doi.org/10.3982/ECTA19978

Johnson, W., & Kieras, D. (1983). Representation-saving effects of prior knowledge in memory for simple technical prose. *Memory & Cognition*, *11*(5), 456–466. https://doi.org/10.3758/bf03196982

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.

Kannan, P. K., & Kopalle, P. (2001). Dynamic Pricing on the Internet: Importance and Implications for Consumer Behavior. *International Journal of Electronic Commerce*, *3*, 63–84.

Kardes, F. R., Cronley, M. L., Kellaris, J. J., & Posavac, S. S. (2004). The Role of Selective Information Processing in Price-Quality Inference. *Journal of Consumer Research*, *31*(2), 368–374. https://doi.org/10.1086/422115

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

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

Kruglanski, A. W., Pierro, A., Mannetti, L., & Grada, E. de (2006). Groups as epistemic providers: Need for closure and the unfolding of group-centrism. *Psychological Review*, *113*(1), 84–100. https://doi.org/10.1037/0033-295X.113.1.84

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

Little, J. D. (1970). Models and Managers: The Concept of a Decision Calculus. *Management Science*, *16*(December), B466-B485.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research*, *46*(4), 629–650. https://doi.org/10.1093/jcr/ucz013

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

Lukas, M. F., & Howard, R. C. “. (2023). The Influence of Budgets on Consumer Spending. *Journal of Consumer Research*, *49*(5), 697–720. https://doi.org/10.1093/jcr/ucac024

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

MacKay, A., Svartbäck, D., & Ekholm, A. G. (2022). Dynamic Pricing and Demand Volatility: Evidence from Restaurant Food Delivery. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.4164271

MacKay, A., & Weinstein, S. (2021). Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Response. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.3979147

Mekki, D. (2022). The Antitrust Division’s Role in Protecting Competition in a Changing Digital Marketplace. Retrieved from https://www.justice.gov/opa/speech/principal-deputy-assistant-attorney-general-doha-mekki-antitrust-division-delivers-0

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

Milgrom, P., & Roberts, J. (1986). Price and Advertising Signals of Product Quality. *The Journal of Political Economy*, *94*(4), 796–821. https://doi.org/10.1086/261408

Monroe, K. B., & Lee, A. Y. (1999). Remembering Versus Knowing: Issues in Buyers' Processing of Price Information. *Journal of the Academy of Marketing Science*, *27*(2), 207–225.

Montjoye, Y., Schweitzer, H., & Crémer, J. (2019). Competition Policy for the Digital Era. Retrieved from https://data.europa.eu/doi/10.2763/407537

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

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

Punj, G. N., & Staelin, R. (1983). A Model of Consumer Information Search Behavior for New Automobiles. *Journal of Consumer Research*, *9*(4), 366–380.

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.

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/

Rook, D. W., & Fisher, R. J. (1995). Normative Influences on Impulsive Buying Behavior. *Journal of Consumer Research*, *22*(December 1995), 305–313.

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

Shiv, B., & Fedorikhin, A. (1999). Heart and Mind in Conflict: the Interplay of Affect and Cognition in Consumer Decision Making. *Journal of Consumer Research*, *26*(3), 278–292. https://doi.org/10.1086/209563

Simonsohn, U. (2009). Direct risk aversion: Evidence from risky prospects valued below their worst outcome. *Psychological Science*, *20*(6), 686–692. https://doi.org/10.1111/j.1467-9280.2009.02349.x

Slovic, P. (1987). Perception of risk. *Science (New York, N.Y.)*, *236*(4799), 280–285. https://doi.org/10.1126/science.3563507

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

Stamatopoulos, I., Bassamboo, A., & Moreno, A. (2021). The Effects of Menu Costs on Retail Performance: Evidence from Adoption of the Electronic Shelf Label Technology. *Management Science*, *67*(1), 242–256. https://doi.org/10.1287/mnsc.2019.3551

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

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

United States (2018). Personalized Pricing in the Digital Era – Note by the United States. Retrieved from https://one.oecd.org/document/DAF/COMP/WD(2018)140/en/pdf

Vermeir, I., van Kenhove, P., & Hendrickx, H. (2002). The influence of need for closure on consumer's choice behaviour. *Journal of Economic Psychology*, *23*(6), 703–727. https://doi.org/10.1016/S0167-4870(02)00135-6

Victor, V., Thoppan, J. J., Nathan, R. J., & Fekete-Farkas, M. (2018). Factors Influencing Consumer Behavior and Prospective Purchase Decisions in a Dynamic Pricing Environment—An Exploratory Factor Analysis Approach. *Social Sciences*, *7*(9), 153. https://doi.org/10.3390/socsci7090153

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

Woodcock, R. (2019). Price Discrimination as a Violation of the Sherman Act. *Connecticut Law Review.* Advance online publication. https://doi.org/10.2139/ssrn.2972369

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

Zeelenberg, M. (1999). Anticipated regret, expected feedback and behavioral decision making. *Journal of Behavioral Decision Making*, *12*(2), 93–106. https://doi.org/10.1002/(SICI)1099-0771(199906)12:2<93::AID-BDM311>3.0.CO;2-S

Zhang, S., Mehta, N., Singh, P. V., & Srinivasan, K. (2021). Frontiers: Can an Artificial Intelligence Algorithm Mitigate Racial Economic Inequality? An Analysis in the Context of Airbnb. *Marketing Science*, *40*(5), 813–820. https://doi.org/10.1287/mksc.2021.1295

Web Appendix [will be a separate document at the end]

Web Appendix A: Survey

Introduction of algorithms

In this short survey, we will ask you about **pricing algorithms** your company may use. A "pricing algorithm" is a detailed set of rules, often implemented by a computer program, that sets prices automatically.

How familiar are you with the price setting strategies in your company.

(Highly familiar – Not familiar at all (five point scale))

Does your company use **pricing algorithms** to set the prices of your products automatically?
- Yes, we use software developed Internally
- Yes, we use software developed by third-parties
- Yes, we follow a detailed set of rules, but implement them without the help of software.
- No, we do not use algorithms or detailed rules when we set prices

How extensively is algorithmic pricing used in your company?

- not used for any products
- used for some products
- used for most products
- used for all products

When did your company begin using algorithmic pricing?'

- least 5 years ago
- in the last 3-5 years
- in the last 1-2 years
- in the last 6 months
- never, we do not use algorithmic pricing

How closely are the pricing **managers at your firm involved** in price setting? (select one)

- Not at all: an algorithm sets prices automatically, without human involvement
- Programming only: the managers only set the algorithm rules, but the algorithm then sets prices automatically
- Partial involvement: managers set the algorithm rules, and then spot-check and adjust the prices suggested by an algorithm
- Final authority: the algorithm only suggests prices, managers then finalize them and make the final decision.
- Complete control: managers carry out the price-setting process on their own, without any algorithmic help or suggestions.

How **often** does your firm change prices? (select one)

- Continuously
- Hourly
- Daily
- Weekly
- Monthly
- Quarterly
- Yearly
- Less than yearly

Which description best captures how **your company in general** varies prices across customers and geographies in general?

- Individualized to each customer
- Customized and different for every geographic market and every customer segment
- Customized for different customer segments
- Customized for different geographic markets
- Uniform across geographic markets and customer customers
- Neither, different parts of the company use different price variation)

Please give a short description of your firm's specific product or service, for which you are the most familiar with the pricing strategy: ______________________

Now consider your firm's **specific product or service, for which you are the most familiar** with the pricing strategy (previous question). Which description best captures how prices for this specific product or service vary across customers and geographies?

- Individualized to each customer
- Customized and different for every geographic market and every customer segment
- Customized for different customer segments
- Customized for different geographic markets
- Uniform across geographic markets and customer customers

Please consider your company's key competitors. What best describes their use of algorithmic pricing as it compares to your firm?

- Our competitors do not use algorithmic pricing
- Our competitors use algorithmic pricing, but our solution is better than theirs
- Our competitors use algorithmic pricing in a similar way to us
- Our competitors use algorithmic pricing, and our solution is worse than theirs
- I do not know whether our competitors use algorithmic pricing

Based on your own understanding of what pricing algorithms are and how they work, please indicate the extent to which you agree with the following statements.
I think that pricing algorithms…
(Five point scale from "Completely agree" to "Completely disagree")
Order randomized:

Pricing algorithms:

- lead to less competition.
- lead to increased competition.
- make price setting easier
- make price setting more efficient
- reduce the chance of error
- result in increased personalized pricing,
- make pricing less transparent
- are a black box
- provide less control over pricing decisions.
- increase profit maximization
- cannot be trusted
- are perceived to be fair by consumers
- are liked by consumers

The following two questions only if respondent does not answer "No" to the second question (i.e. Does your company use pricing algorithms?):

Which of the following are the **inputs** to the pricing algorithms your company uses?
(___Yes ___No __Do not know)
Order randomized:

- Your firm's costs, such as production, storage and fulfilment.
- Your firm's past revenue or profit data
- Competing firms' prices
- Past consumer behavior data, such as purchase or browsing history
- Other consumer data, such as demographics, geographics
- External information, such as macroeconomic trends or weather patterns
- Other. Fill in:_______________

Which of the following are the **methods or rules** the pricing algorithms your company uses?
(___Yes ___No __Do not know)
Order randomized:

- "Win-Continue Lose-Reverse" rule
- Q-learning
- Artificial neural networks (ANN)
- Deep learning
- Adaptive machine learning
- Unsupervised or reinforcement learning
- Other. Fill in:_______________

Thank you for sharing your experience with pricing algorithms. Before we finish, we will now ask a few questions about you and your company.

What is your position in your company?

- staff / employee
- mid-level manager (in charge of running the company)
- top-level manager (make decisions how the company operates)

Are you in charge of pricing decisions at your firm? (yes/no)

Location of your company?

- European Union
- United States of America
- Asia Pacific region
- Other

What proportion of sales in your company are through online channels?

- less than 25%
- 25 – 50%
- Greater than 50%

In which of the following classification does your company fall?

Agriculture, Forestry, Mining [primary sector]
Industrials (Manufacturing, Construction, etc.) [secondary sector]
Energy, Utilities [secondary sector]
Transport, Logistics, Warehousing [tertiary sector]
Media, Creative Industries [tertiary sector]
Data Infrastructure, Telecom [tertiary sector]
Healthcare [tertiary sector]
Education [tertiary sector]
Life Sciences [tertiary sector]
Retail / ecommerce [tertiary sector]
Hospitality, Food, Leisure Travel [tertiary sector]
Public Service, Social Service [tertiary sector]
Financial Services, Insurance, Real Estate [tertiary sector]
Professional Services (Law, Consulting, etc.) [tertiary sector]
Other (Arts, Food, Other)
Wholesale Trade
Charity and Non-profit
Leisure, sport or tourism
Marketing, advertising or PR

What market does your company serve?

- businesses,
- consumers
- both

What is the total number of permanent employees in your company?

- 1 - 19
- 20 - 49
- 50 - 99
- 100 - 249
- 250 -499
- 500 - 999
- 1,000 - 2,500
- Over 2,500

What is the age (years in business) if your company?

- 0-5
- 6-10
- 11-20
- >20

Web Appendix B: Survey Results

Table A1 illustrates pricing practices for firms that have implemented pricing algorithms and those that have not.

Table A1: Pricing practices by firms with and without pricing algorithms (Survey)

	Pricing Algorithms used	
How often does your firm change prices?	No	Yes
1= continuous	0.037	0.130
2 = hourly		
3 = daily	0.074	0.148
4 = weekly	0.074	0.074
5 = monthly	0.000	0.148
6 = quarterly	0.296	0.222
7 = yearly	0.333	0.167
8 = less than yearly	0.111	0.074
Customize		
Individualized to each customer	0.316	0.243
Customized geographically and each consumer segment	0.368	0.432
Customized for different segments	0.105	0.054
Customized for different regions	0.211	0.162
Uniform across segments and geographic regions	0.000	0.108
varies prices across customers and geographies		
Individual to each consumer;	0.259	0.167
Geographically and each consumer segment	0.333	0.352
Customized for different segments	0.111	0.130
Customized for different regions	0.111	0.167
Uniform across segments and geographic regions	0.000	0.111
Different parts of the company use different price variations	0.185	0.074

Table A2 shows that companies most widely use their cost data (75.7%) and past revenue or profit data (73%) as inputs for pricing algorithms. Perhaps surprisingly, 43.2% of firms do not use information about competitors' prices, and slightly less than half of the companies do not use information helpful for customizing prices to individual consumers. Regarding the type of rules, "Win-Continue Lose-Reverse" and adaptive machine learning are the most widely used methods.

Table A2: Data and type of method used for pricing algorithm (Survey)

Data used for Pricing Algorithm (most familiar product)	**Proportion**
Your firm's costs	0.757
Your firm's past revenue or profit data	0.730
Competing firm's prices	0.568
Past consumer behavior	0.541
Demographics and Geographics	0.595
External info	0.405
Type of Pricing Algorithm (method or rules used)	**Proportion**
"Win-Continue Lose-Reverse" rule	0.297
Q-Learning	0.135
Artificial neural networks	0.054
Deep learning	0.135
Adaptive machine learning	0.270
Unsupervised or reinforcement learning	0.108

To identify the factors influencing the extent of pricing algorithm usage, we employed regression analysis, examining managers' perceptions of pricing algorithm attributes in relation to the extent of algorithm usage. Specifically, we considered 12 attributes specified in Question "I think that pricing algorithms…" (see Table A3). As a first step we conducted factor analysis on these attributes and retained three factor scores for subsequent analysis.

The results of the Factor analysis are provided in Table A3. Factor 1 pertains to the drawbacks associated with pricing algorithms, such as their opaqueness, lack of trustworthiness, and diminished control. Factor 2 includes consumer believes, including consumer preference and perceived fairness. Factor 3 is associated with the benefits of algorithms, such as their ease of use, efficiency, error reduction, and profit enhancement.

Next, we estimate a logistic regression with the extent to which their company uses pricing algorithms as the dependent variable and the three factors as explanatory variables (see Table A4). The results indicate that drawbacks associated with pricing algorithms (Factor 1) have a negative association with the extent of usage of pricing algorithms. Especially, pricing algorithms are perceived to lead to less control over pricing decision, though trust and "are a black box" also play a role. Managers' perceptions of consumers' beliefs (Factor 2) are positively associated with pricing algorithms. That is, managers who use pricing algorithms less extensively believe that consumers like them less and perceive them to be less fair. However, surprisingly, benefits of pricing algorithms are also associated with lower usage of pricing algorithms. A further examination into this result indicates that managers who have not adopted pricing algorithms tend to overstate the benefits, compared to those who do use pricing algorithms.

Overall, these results suggest that the reluctance to implement pricing algorithms is not due to a misunderstanding of their benefits. On the contrary, it seems to stem from negative perceptions surrounding pricing algorithms, such as reduced transparency and managerial control, along with negative consumer perceptions.

Table A3: Results of factor analysis (Survey)

	Factor1[a]	**Factor2**	**Factor3**
Lead to increased competition	-0.019	-0.022	0.462
Make price setting easier	0.083	0.484	0.591
Make price setting more efficient	-0.135	0.054	0.760
Reduce the chance of error	-0.187	0.580	0.477
Results in increased personalized pricing	0.168	0.037	0.524
Make pricing less transparent	0.439	-0.299	-0.211
Are a black box	0.763	-0.339	0.176
Provide less control over pricing decisions	0.782	-0.043	-0.112
Increase profit maximization	-0.277	-0.075	0.632
Cannot be trusted	0.807	0.190	-0.023
Are perceived to be fair by consumers	-0.022	0.808	-0.094
Are liked by consumers	-0.080	0.824	-0.008

[a] Rotated factor scores using Varimax rotation.

Table A4: Results of logistic regression of managers' perceptions on extent of usage of pricing algorithms (Survey)

Parameter	**Estimate**	**s.e.**	**p-val.**

$Intercept_1$	-0.6879	0.2726	0.0116
$Intercept_2$	0.6913	0.2728	0.0113
$Intercept_3$	2.3451	0.4025	<.0001
Factor1	0.788	0.2534	0.0019
Factor2	-0.5336	0.2431	0.0281
Factor3	0.5764	0.2375	0.0152

Web Appendix C: Case Study

Figure A1 displays some examples from the partner company. The price sign next to the product is a digital screen, the ESL.

Figure A1: Electronic shelf labels (ESL)