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Dynamic pricing: Definition, implications for managers, and future research directions ☆

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Abstract

Dynamic pricing has evolved with technology from earlier price negotiations. To maximize revenue and provide specialized shopping experiences, businesses today use algorithms and data analysis to adapt prices. We define dynamic pricing as price changes that are prompted by changes or differences in four key underlying market demand drivers: (1) People (i.e., individual consumers or consumer segments), (2) Product configurations, (3) Periods (i.e., time), and (4) Places (i.e., locations). The transition from static pricing (uniform prices) to dynamic pricing (changing prices) is evident from different examples, such as online retailers personalizing offers based on customer behavior, and algorithms using facial recognition for personalized pricing in physical stores.

Fueled by AI and machine learning algorithms, dynamic pricing is transforming industries from transportation to e-commerce, optimizing revenue and enhancing customer experiences. While it offers benefits like personalization, challenges include ethical concerns, cost of implementation, and customer dissatisfaction. Effective data organization and AI expertise are crucial, but potential pitfalls and regulatory oversight must also be considered. This paper examines the multidimensional application of dynamic pricing, highlights the adaptability and efficiency of dynamic pricing in forming profitable pricing strategies and maximizing revenue, and calls for continued research on the topic to balance revenue, customer satisfaction, and ethics.
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Dynamic pricing originated in the early history of commerce, when merchants would engage in price negotiations influenced by variables such as the buyer's social standing and negotiation prowess, available inventory, or the volume of goods being bought. In contemporary times, the concept of dynamic pricing is becoming more salient and sophisticated with the advent of technology. Firms today are employing algorithms and data analysis to customize prices according to factors such as product configurations, browsing habits, market competition, geographic location, and past buying patterns. This approach enables firms to present varying prices for more or less "identical" products based on factors such as demand, product quality and availability, and individual customer attributes. As a result, businesses are optimizing their revenue while delivering personalized shopping experiences.

Price discrimination has been studied extensively in economics. The definition by Stigler (1987), as noted by Stole (2007; p. 2224–2225), highlights that "a firm price discriminates when the ratio of prices is different from the ratio of marginal costs for two goods offered by a firm." This definition is augmented by various theoretical models such as: intrapersonal price discrimination, purchase-history price discrimination, second- and third-degree price discrimination, non-linear pricing, and bundling (Stole 2007). However, managers may view the three degrees of price discrimination as more theoretical in nature, and strive to incorporate more practical considerations. A product's price not only yields

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current economic information, it also evokes past prices (see reference price research) and emotions that can have a longer-term impact on the future revenue stream for the company, as demonstrated across examples in this paper. Pricing research in marketing has excelled in acknowledging and integrating these multiple perspectives, and paves the way for new research to update our understanding.

It should be noted that demand estimation, elasticity, and willingness to pay are at the heart of profitable pricing strategy. For instance, in the context of for grocery retailers, Srinivasan et al. (2008) demonstrate that demand considerations lead to higher profits than changing prices week-to-week based on wholesale costs and competition. Dynamic pricing takes it to the next level by micro-segmenting the market based on people, products, periods, and places, and understanding and estimating the demand at the micro-segment level to adjust prices as the four key dimensions change.

In this paper, our discussion of dynamic pricing is more encompassing and propels price discrimination into the 21st century. It begins with the word "dynamic." The origins of the word "dynamic" lie in the Greek word *dynamis*, which means force. In physics, dynamics is the study of motion. The opposite of dynamic is static, which is derived from the Greek word *statikos*, which means no movement. Therefore, the word dynamic implies some change or movement. Accordingly, "dynamic pricing" implies changes or movements in prices, and static pricing implies no change or movement in prices.

Consider the case of how a vegetable vendor in Hyderabad, India, sells his products using dynamic pricing. Every morning, the vendor goes to the local wholesale market known as a *mandi*, buys and fills his cart with various vegetables and greens, then pushes his cart through the streets of Hyderabad selling his vegetables. The cart does not display the prices of the various vegetables and greens. And the vendor does not roam the streets randomly to sell his goods. Instead, he first pushes his cart through the most affluent neighborhoods. As potential buyers show up in front of his cart, he sizes up the individual plus the house they came from, including the types of vehicles parked at their house, and then quotes his price based on his assessment of how price insensitive the buyer is. By early afternoon, he moves his cart to the less wealthy neighborhoods and reduces the price quote for vegetables and greens accordingly, as he knows from experience that the consumers in those neighborhoods are more price sensitive than those in the affluent neighborhoods. By late afternoon, all the good vegetables and greens have been picked and the sun has taken a toll on the remaining products. At that time, the vendor begins to push his cart through the poorer neighborhoods of the city and sells the remaining wares at prices just above the price he paid for them in the *mandi*.

The fundamental concept highlighted in the above example is the recognition that the conventional one-size-fits-all approach of static pricing can be improved through micro segmentation across multiple dimensions. Technological advancements, abundant data, and sophisticated algorithms have empowered retail managers with the capability to adapt flexible pricing that accounts for underlying differences in price sensitivity of demand and willingness to pay across multiple segments at a large scale.

The rest of the paper is organized as follows. We begin with our definition of dynamic pricing, followed by the four key dimensions of dynamic pricing:we refer to them as the "4 Ps" of dynamic pricing—(i) People, (ii) Product, (iii) Period, and (iv) Place—that influence the price sensitivity of demand. Finally, we conclude with directions for future research.

A working definition of dynamic pricing

The need to start with a definition of dynamic pricing is made evident by the striking difference in opinions we find in practice. To start, Wikipedia claims "dynamic pricing, also referred to as surge pricing, demand pricing, or time-based pricing, is a pricing strategy in which businesses set flexible prices for products or services based on current market demands" (Wikipedia). But others view dynamic pricing as "the (fully or partially) automated adjustment of prices" (McKinsey); as "a strategy in which the price of an item is constantly and automatically adjusted in response to real-time changing demand" (Inc.com); or an approach for individual products or services "that utilizes variable prices instead of fixed ones" (Paddle). Moreover, industry experts argue that "the main idea behind dynamic pricing is that it is flexible and based on real-time data" (Business.com), and that "a strong dynamic pricing strategy relies on the power of the algorithm used to generate pricing" (Wall Street Journal, Deloitte). They also advise companies to invest in "a technique to build price architecture to ensure all pertinent price drivers are fairly represented in pricing decisions" (Simon-Kucher and Partners), and even portray the challenge as a destination where "companies use AI to analyze numerous inputs in near real time to generate pricing outputs that can be tailored all the way down to the individual customer level" (BCG). This is just a small selection of the explanations we encountered.

We define dynamic pricing as changes in price that are prompted by changes or differences in four key underlying market demand drivers: (1) People (i.e., individual consumers or consumer segments), (2) Product configurations, (3) Periods (i.e., time), and (4) Places (i.e., locations). In other words, dynamic pricing fine-tunes prices to accommodate variations in price sensitivity of demand across micro-segments based on consumers, products, periods, and places. Of course, in each of the four cases, there will be competitive forces at play. The changes in the competition are captured in changes in period and place dimensions and accounted for in the willingness to pay, price elasticity, and demand estimation. We posit that dynamic pricing, as applied in the context of companies, is a question of degree, whereas "Static Pricing" is a special case indicating a uniform price across people, products, periods, and places. Below, we highlight exemplars of dynamic pricing based on changes in each of these drivers.

The first dynamic pricing driver is the change in prices due to *changes (or differences) across people or consumer segments* (keeping the place, period, and product the same.) For example, the rapid development of information technology has enabled sellers to customize current offers based on individual consumers' previous purchase behavior (Fudenberg and Tirole 2000; Zhang 2011, and Acquisti and Varian 2005). This is made possible through computer-mediated transactions and real-time access to databases. The online environment provides various mechanisms, such as cookies, unique identifiers, and direct user authentication, which allow the collection and analysis of consumer data (Choe et. al. 2018). As a result, industries such as supermarkets, airlines, and credit cards have compiled vast databases of individual consumer transactions to study purchasing patterns and offer personalized incentives through targeted marketing strategies. While some argue that consumers served with higher prices may defect to competition, which may lead firms to abandon price sensitivity based dynamic pricing, such changes in pricing due to differences in customer segments remain profitable for firms even in the presence of informed customers (Li and Jain 2016; Laussel and Resende 2022).

Progress in information technology has increasingly streamlined the implementation of algorithmic pricing, a significant aspect—though not obligatory—of dynamic pricing. Take facial recognition, for instance, which can algorithmically support dynamic pricing in physical environments on a per-consumer basis. This technological application might furnish brick-and-mortar establishments with an extra edge over their online counterparts, as it proves more challenging to evade in-store, enhancing the dependability of algorithms. This stands in contrast to various algorithms used in online contexts that rely on cookies or user account details, susceptible to bypassing through actions like clearing cookies or using alternative/guest accounts.

The second dynamic pricing driver is price changes due to changes in *product configurations*. A good example of changes in a product configuration that could prompt a price change is a change in product quality. In other words, while the origin and the destination are the same for a particular airline route, the first-class service may have flat-bed seats, while the second-class could have seats that will recline only a little. Thus, while the rest of the three dimensions (place, people, and period) remain constant, prices change due to a change in product configuration. This means the same customer at the same time and same location has the option of buying different product configurations at different prices.

In the third dynamic pricing driver, *price changes over time* (keeping location, product quality, and customers the same). For example, demand could be a function of internal or external reference prices (Greenleaf 1995; Kopalle, Rao, and Assuncao, 1996, and Arora 2012; Briesch, Krishnamurthi, Mazumdar, and Raj 1997). Typically, reference price formation is characterized as an adaptive expectation process and operationalized as the exponentially smoothed value of past prices, and the impact of reference price on demand is expressed as the difference between the reference price and the observed price. When the reference price is more (less) than the observed price, customers perceive a gain (loss), and demand increases (decreases) by an amount that is a function of this difference. A rich literature in marketing (Kopalle and Lindsey-Mullikin 2003; Kopalle and Winer 1996; Winer 1986) shows that understanding this process may yield the most advantageous dynamic pricing tactics for firms. For instance, an increase in the current price of a brand leads to a future benefit to that brand because increasing the future reference price reduces the impact of a price increase and enhances the impact of a price decrease. Likewise, temporary price reductions increase overall sales when the impact of a gain is greater than that of a loss, which typically happens when most consumers are promotion-, rather than prevention-focused (Alkis et al. 2023).

Another example of time-based dynamic pricing is employed by firms offering capacity-constrained and perishable services, such as apparel, retail transportation, and hotels (Talluri and Ryzin 2006). Companies like Uber and Lyft adjust prices in response to real-time supply and demand dynamics. Similarly, apparel retailers employ markdown pricing strategies that respond to shifts in popularity and changing fashion trends over time. The core concept behind these strategies is to align available inventory with anticipated demand at any point in time: prices increase when expected demand surpasses inventory, and they decrease when supply exceeds demand.

Finally, outlet stores demonstrate the phenomenon where prices change for similar products as *places* change, keeping period, people, and products constant. Such stores are located in malls at a significant distance from the shopping districts of major metropolitan areas. The motivation for such dual or segmented distribution is related to differences between consumers' cost of search and accessibility. In other words, outlet malls attract price-sensitive searchers and non-service-sensitive consumers, leaving more service-sensitive (and less price-sensitive) time constrained consumers in the primary location.

We will now delve more deeply into each of the dynamic pricing drivers. Overall, to understand the four key dimensions of dynamic pricing, we have provided examples from the industry and created our "4 Ps" (Products, People, Periods, and Places) of dynamic pricing framework in Fig. 1 and provided exemplar companies based on their respective dynamic pricing strategies. Table 1indicates how certain companies have utilized dynamic pricing.

Dynamic pricing due to differences across people (or customer segments)

The typical bases for customer segmentation are geographic (e.g., location, climate, population density), demographic (e.g., age, income, education), psychographics (e.g., activities, interests, values, opinion, attitudes) and behavioral (e.g., usage, loyalty, benefits). Kamakura and Russell (1989) pioneered the latent class segmentation where customers are segmented based on their marketing mix responsiveness, particularly with respect to price sensitivity. The increased availability of individual level purchase history data provides the possibility for researchers and managers to es-

Table 1
Examples of implementation dynamic pricing by companies.

Company	Dimensions of Dynamic Pricing covered	Implementation of Dynamic Pricing
Stich Fix	Products, People	Stich Fix is an online styling personal service that implements dynamic pricing based on consumer preferences, purchase history, and feedback.
Nike	Places, Periods	Nike customizes prices based on where it sells the products. The prices are different when sold at a company owned store versus an outlet store.
Delta	Periods, People, Products	Delta determines pricing of their airline tickets based on when the customer is making a purchase, the amenities they opt, their loyalty membership, etc.
Costco	People, Places, Periods	Prices vary at various Costco locations for the same product. Prices also vary based on the membership status of the customers. Over time, the price changes in stores based on seasonality.
Amazon	Periods, Products, Places	Amazon implements dynamic pricing based on product category, market trends, and competitor prices.

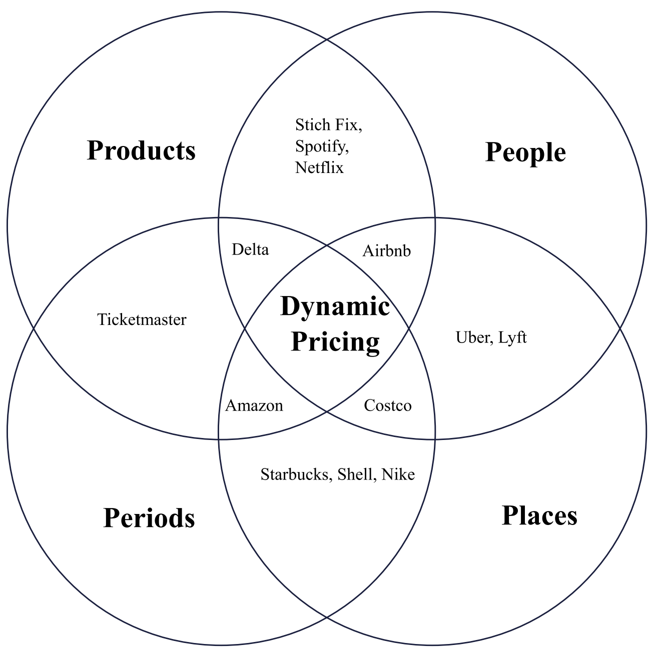

Fig. 1. 4 Ps (Products, People, Periods, Places) of dynamic pricing framework with exemplar companies.

timate price sensitivities at the individual level. Rossi, McCulloch, and Allenby's (1996) results indicate that there is a lot of potential for enhancing firm profitability by using household purchase histories. Their analysis suggests a net gain in revenue from target couponing which is 2 ½ times the gain from blanket couponing and they suggest the use of an electronic coupon as a vehicle to do so.

Kopalle, Kannan, Boldt, and Arora (2012) extend the household level analysis to a pricing context and study the impact of household level heterogeneity in reference price effects on a retailer's pricing policy. For some households, a gain has a higher impact than a corresponding loss, while the opposite is true for others. Using consumer level estimates, Kopalle et al. (2012) develop a normative pricing policy for a retailer maximizing category profit; the corresponding results indicate that the optimal pricing policy derived from the heterogeneous case is qualitatively different, and more profitable, than the case when heterogeneity is ignored.

Another important facet of dynamic pricing due to changes in customer segments is algorithmic pricing. Wang, Li, and Kopalle (2022) define algorithmic pricing as firms' use of artificial intelligence algorithms to recognize and analyze consumers and offer them personalized prices. In the contemporary landscape, businesses, armed with robust big-data analytics, can effortlessly discern consumer preferences by scrutinizing their digital footprint. Target, in the retail sector, tailors personalized coupons based on customers' previous shopping behavior (Perez, 2019). Meanwhile, in travel and hospitality, Orbitz engages in price discrimination by monitoring online browsing activities (Mattioli, 2012), and Starwood Hotels & Resorts employs conversational chatbots to automatically dispatch personalized promotions, prompting consumers to expedite their purchase decisions (Rijmenam, 2017).

The utilization of consumer data extends beyond online sellers to brick-and-mortar retailers. Amazon's cashier-less "Amazon Go" stores, for instance, employ cameras and sensors to recognize and monitor consumers, observe their in-store movements, track their product interactions, and provide tailored coupons (Couponsinthenews, 2018). In China, particularly among luxury brands, stores are adopting cameras at entrances coupled with facial recognition technology to identify individuals, enabling personalized pricing (Wong, 2018). According to Safeway's CEO, Steve Burd, the increasing personalization in offerings may render traditional shelf pricing irrelevant (Choi, 2013).

Moreover, facial recognition software proves beneficial at a segment level by analyzing consumer facial responses to marketing efforts, such as product packaging design or shelf organization. Eye tracking and facial expression analysis aid marketing professionals in understanding how consumers react to specific approaches and what captures their attention. This technology is primarily applicable in physical locations and may not be as viable in online settings due to stringent privacy permissions. Algorithmic pricing, leveraging facial recognition data, enhances the provision of reliable personalized prices and promotions during the shopping experience. It enables the swift identification of preferences for new consumers without prior history and detects transient shifts in tastes and preferences for known consumers while shopping.

It is our thesis that advances in information technologies have further facilitated the use of algorithmic pricing. For instance, algorithmic price discrimination can draw on data from facial recognition in physical settings. This means that, keeping the other three dimensions constant (place, product, and period), two different customer segments who differ in their price sensitivity toward a product may see two different prices.

To illustrate, let us assume that the demand functions for two customer segments for the same product are given by 390 – 0.1p for Segment 1, and 390 – 0.15p for Segment 2. Without loss of generality, say the variable cost of the product is $100. The total contribution margin from the two segments is given by:

$$\pi = (p_1 - 100)(390 - 0.10p_1) + (p_2 - 100)(390 - 0.125p_2)$$

Where p_1 and p_2 are the prices charged to Segments 1 and 2 respectively.

Taking the derivative of the profit function with respect to p_1 and p_2, equating them to zero, and solving them simultaneously yields the optimal prices p_1^*=$2000.002 and p_2^*=$1600.00. Using algorithmic pricing, which can be implemented both in online and offline stores, one way to offer different prices to the two segments is to exhibit a shelf price of $2000.00 for the product and send segment 2 a coupon for $400.00.

Dynamic pricing due to changes in product configurations

One of the avenues to apply dynamic pricing is via offers of product lines. With a single product configuration, firms are generally constrained in terms of their implementation of dynamic pricing and gravitate toward more static pricing. One problem with static pricing is that the firm may leave money on the table, i.e., some customers may be willing to pay more for the product or service. A second concern is that the firm may be passing up some profit. More specifically, some customers will not be served even though the firm could have served them at prices above the variable cost. To further examine this issue, let us assume that a product's (say, an airline) sales response curve is expressed by the graph in Fig. 2 below.

If the airline were to determine an optimal single price, we can derive it as shown in Fig. 3:

The optimal single price would be calculated by taking the partial derivative of the profit function, (p-100)(390–0.1p) with respect to price, p, setting it equal to zero, and solving for the price. That would yield an optimal price of $2000.00. As seen in Fig. 3, the top triangle to the right of the variable cost line and above the shaded area is passed-up sales —i.e., the unmet demand—and the bottom triangle to the right of the shaded area is leaving money on the table.

Now let us consider the airline changing its product configuration from a single class of service to two classes of service: economy and first-class, as shown in Fig. 4 below, where the first-class seats may be converted to a flat-bed configuration when needed. The airline will charge a price of p_H for first-class and p_L for the economy class.

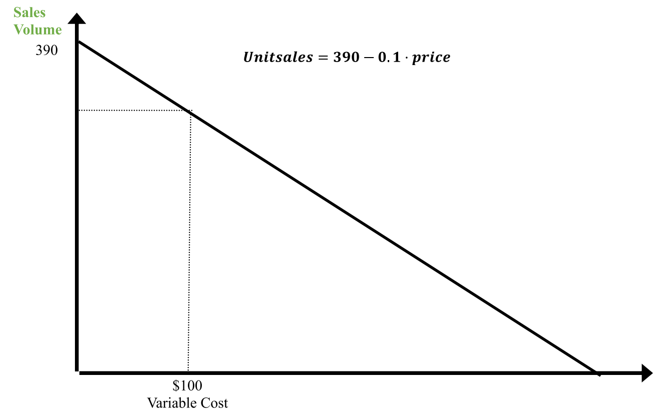

Fig. 2. Airline sales response curve.

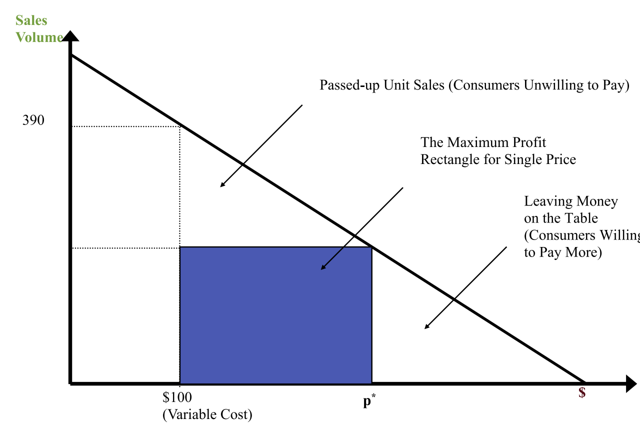

Fig. 3. Airline pricing with a single price.

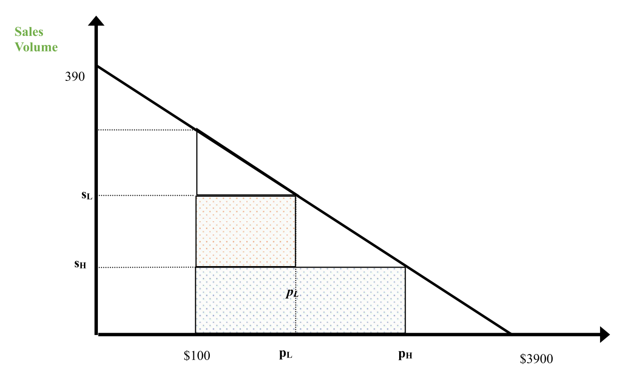

Fig. 4. Pricing with two classes of service.

The question now is: how do we arrive at prices p_H and p_L for the first class and economy product configurations? The key here is to maximize the total area of the two rectangles, which is the total profit generated from both economy and first-class product configurations. The total profit is given by π=(p_H −100)s_H + (p_L −100)(s_L- s_H), where s_H=390–0.1 p_H and s_L=390–0.1 p_L. Simplifying, we get, $\pi = 390p_H - 0.1p_H^2 - 3900 + 10p_L + 0.1p_Hp_L - 0.1p_L^2 + 10p_L$. Taking the derivate of the profit function with respect to p_H and p_L and equating each to zero we get: 390–0.2 p_H+0.1 p_L = 0 and 0.1 p_H - 0.2 p_L + 10 = 0.

Table 2
Comparison of two-class and one-class pricing.

	Single Class	First and Economy Class
Price	$2000	$1367.00 and $2633.00
Sales Volume	190	127 First class and 127 Economy
Contribution	$361,000	$481,330 (+34%)

Table 3
Cell phone pricing.

Customer Segment	Voice Mail	Text Messaging	Both
1	9.00	1.50	10.50
2	8.00	5.00	13.00
3	4.50	8.50	13.00
4	2.50	9.00	11.50

Solving the two equations simultaneously will yield p_H =$2633.00 and p_L =$1367.00. The comparison is shown in Table 2 below.

A key condition for the success of such a dual-pricing tactic is that the product configuration for the first-class seat is significantly better than that of an economy seat, such that all consumers prefer the best class they can afford. There is a rich marketing literature on product lines and product line pricing. The optimal design of a product line has been a core question in the product line literature dating back to the seminal article by Mussa and Rosen (1978) (see also Carlton and Dana 2008, Che and Wang 2010, Dobson and Kalish 1988, Johnson and Myatt 2003, Krishnan and Zhu 2006, Moorthy 1984, Villas-Boas 2004, and Biyalogorsky and Koenigsberg 2014, Kopalle and Winer 1996). In these models, consumers differ in how much they value product quality. The firm knows the distribution of consumer tastes for quality but cannot identify the taste of individual consumers. These articles determine the optimal product line to offer to consumers such that the firm's profit will be maximized. These models consider both simultaneous and sequential introduction. The papers that consider sequential introduction (Moorthy and Png 1992 and Biyalogorsky and Koenigsberg 2014) deal explicitly with dynamic pricing. The papers that consider simultaneous introductions assume different prices for different products, and each targets different consumer segments.

Multi-product pricing - pure and mixed bundling

Another common example of price changes due to changes in product configuration is bundling. Consider a cell phone pricing case for two add-on services: voice mail and text messaging. As seen in the Table 3, let's say there are four customer segments of equal size, each with a different willingness to pay per month. For simplicity, assume zero variable costs.

If the firm were to sell voice mail and text messaging as pure components, the optimal voice mail (text messaging) price would be $8 ($8.50), for a total profit of $33.00 with Segments 1 and 2 purchasing voice mail alone and Segments 3 and 4 buying text messaging only. If the firm were to offer a pure bundle, the optimal bundle price would be $10.50 with a profit of $42.00 with all four segments purchasing the bundle.

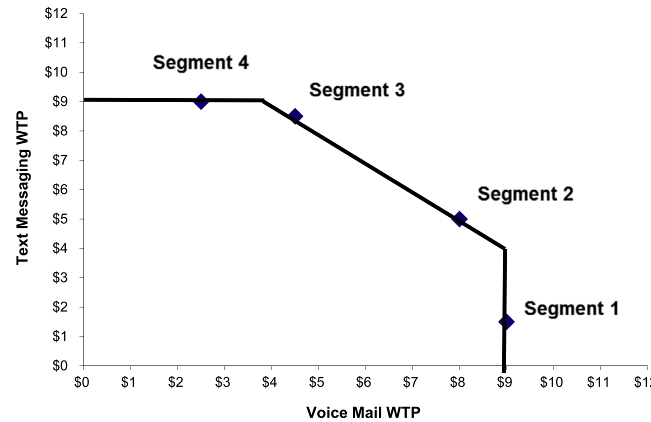

Fig. 5. Graphical solution to bundling problem.

The question then is whether the firm is better off offering a mixed bundle. Let's start by pricing each item at the highest any segment is willing to pay and pricing the bundled option at higher than $10.50. We can see that at a price of $9.00 each for voice mail and text messaging, and a bundle price of $13.00, the firm's profitability increases to $44.00, with Segment 1 buying voice mail, Segment 4 purchasing text messaging, and Segments 2 and 3 buying the bundle. Graphically, the solution is given in Fig. 5.

In essence, offering a mixed bundle type of a product configuration and changing the price based on the product configuration, such that voice mail and text messaging are priced at $9.00 each and the bundle priced at $13.00, maximizes the firm profitability. That is, as seen in Table 4 and Fig. 5, pricing based on a mixed bundling type of a product configuration can improve profitability.

Pricing for digital goods: access vs. usage-based

Numerous companies are embracing the "servicification" idea where they offer products as a service, often referred to as "anything as a service" or "XaaS." The consumers of these products and services have diverse preferences in terms of the number of items they want and the value they attribute to each item. Firms that create these revenue models can present either a fee based on usage per unit, or a fee based on access over a specific period, akin to pure bundling. In addition, they often combine these approaches into a nonlinear two-part and three-part pricing strategy, applying both types of fees to all buyers (Bhargava and Gangwar 2018; Balasubramanian et al. 2015; Grubb 2009) commonly seen in the telecom industry. Alternatively, a firm can target light and heavy users of products by allowing them to choose from a range of plans that involve per-unit or per-period charges. Gangwar and Bhargava (2023) analyze alternative ways of combining access and usage-based pricing and find that providing consumers with the flexibility to choose between per-

Table 4
Pricing based on product bundling.

	Optimal Prices Text			Sales Volume Text			Profit	Profit Index
Pricing structure	Voice mail	Messaging	Bundle	Voice mail	messaging	Bundle		
Pure Components	\$ 8.00	\$ 8.50	NA	2	2	0	**\$ 33**	**100**
Pure bundling	NA	NA	\$ 10.50	0	0	4	**\$ 42**	**127**
Mixed bundling	\$ 9.00	\$ 9.00	\$ 13.00	1	1	2	**\$ 44**	**133**

unit and per-period pricing generates significantly higher market coverage with little loss to revenue.

Dynamic pricing over periods

Changing price over time (keeping location, product configuration, and customers the same) is another important dimension of price dynamics. The first decision a firm has to make is whether or not to change price over time at all. Indeed, doing so requires effort and may lead to customer backlash, as when Apple decided to cut its iPhone price from \$599 to \$399 in 2007 and faced many angry early adopters (cultofmac.com). Even without such backlash, price inertia is common when the costs of price adjustments are high and the benefits low for the retailer. Srinivasan et al. (2009) find high costs in categories with many stock keeping units (high complexity) and higher price levels, indicating a low price and deal sensitivity. Likewise, the benefits of changing prices are lower in categories with lower penetration, and for brands with smaller market share.

Brands regularly change prices in relatively mature fast-moving consumer goods categories due to competitive considerations. Some consumers are loyal to brands, but many consumers switch brands based on lower prices. According to Google's Global Retail Study, 87% of consumers surveyed indicated that knowing they got a good deal was important in their purchasing decision. To attract these price sensitive consumers, firms engage in regular price changes (Narasimhan 1988). This strategy (in online and offline markets) is often used to increase short-term market share by attracting more customers. However, for this strategy to be effective, firms should understand the competitive landscape, market price sensitivity and brand loyalty, and consumer purchase behavior (Gangwar et al. 2014; Van Heerde et al. 2003; Raju et al. 1990; Pauwels 2004). Rao, Arjunji, and Murthi (1995) provide the empirical generalizations of competitive pricing strategies. Gangwar et al. (2014) and Gangwar et al. (2021), analyze markets where loyal consumers exhibit strategic behavior and stockpile goods for future consumption at lower prices and argue that dynamic pricing remains the best response strategy.

So, what are the benefits of changing prices over various time periods? Nijs, Srinivasan, and Pauwels (2007) find that such a practice is associated with higher retailer category margins, especially when prices change for demand-related reasons. Especially temporal price reductions are considered a useful way to sell excess inventory (e.g., Neslin 2002) and appeal to deal-sensitive buyers who cherry-pick price promotions, without having to lower regular prices (Pauwels, Hanssens, and Siddarth 2002). Moreover, temporary price reductions convey an urgency (buy now as long as the deal lasts!) and offer a risk premium to buy unfamiliar products, which the consumer may like and stay loyal to even when prices return to regular levels (Slotegraaf and Pauwels 2008; Kopalle, Mela, and Marsh 1999). However, while the temporal price drop is considered a gain by consumers, the subsequent price increase is considered a loss, and the net effect depends on the situation.

This tradeoff brings us to the important area of dynamic revenue management in the face of reference prices, i.e., what a customer expects to pay for the brand. In the received wisdom that losses loom larger than gains vis-à-vis the reference price (Gal and Rucker 2018), temporary price reductions would result in a net sales loss (Winer 1986; Erdem, Mayhew and Sun 2001). However, evidence for loss aversion in pricing is mixed (Greenleaf 1995; Kopalle, Rao, and Assuncao, 1996; Kopalle, Kannan, Boldt, and Arora 2012; Kopalle and Winer 1996; Pauwels, Srinivasan and Franses 2007; Bell and Lattin 2000; Kalwani et al. 1990; Mazumdar and Papatla 1995; Klapper et al., 2005) and Gal and Rucker (2018) point to price response asymmetry as a real-world phenomenon where loss aversion does not hold. Instead, Alkis et al. (2023) offer a market-level interpretation of regulatory focus theory as an overarching explanation, identifying observable (to managers) conditions under which they may expect most consumers to react stronger to gains than to losses. One such condition is labor market resilience, which amplifies consumers' promotion focus, in which gains are more important than losses. Through an analysis of 2178 brands in 742 retail stores across 50 U.S. metro areas, they indeed find that price decrease response accentuates, whereas price increase response attenuates, as labor markets become more resilient. On average, when price is lowered by 10%, sales increase by 14.3% at the median level of labor market resilience. When price is increased by the same amount, sales decrease by 8.7%.

Implications of temporal changes in price for consumer store experience

After uncovering short-term consumer response to price changes, how do we leverage dynamic pricing to enhance consumer experience in the store? The most obvious answer would be to present prices that favorably compare to the consumer's reference price. In such situations, the consumer may not only buy more products, but also favorably update the price image of the store (van Heerde et al. 2008). However, permanently lowering prices hurts retailer profits and may start a price war (ibid), while temporary price reductions imply a return to regular prices, which will appear like a loss to the consumer. Therefore, increasing reference prices is a way to provide a perception of "gain" in the minds of the customer, and is practiced by about a quarter of Amazon sellers (Park, Xie, and Xie 2023): "We found that by increasing the price by 23% on average, the seller achieves a 15% advantage in their sales rank among all products in the home and kitchen category." However, consumers rightfully become upset when they figure out this deceptive practice. Another way to use dynamic pricing is to uncover which consumers are more likely to tolerate high prices and enjoy gains and to ensure the retailer attracts and retains those consumers.

Price changes over time based on supply and demand mismatch

Often dynamic pricing over different periods is driven by limited inventory consideration and is widely popular in a few industries, such as airlines, cruises, and hospitality. It evolved primarily from supply and demand fundamentals to personalized pricing strategies and was adopted in industries such as transportation, vacation rentals and real estate markets using consumer price elasticity (Joo, Gauri, and Wilbur 2020). For example, the airline industry has been using inventory-based revenue management since 1970 after the deregulation of the U.S. airline market. Many sophisticated algorithms to automate pricing decisions have been devised in the recent past (Talluri and Ryzin 2006). These techniques rely critically on firms' ability to forecast demand and price elasticities based on analyzing historical data to predict future demand (For more on determinants of price elasticity, see Bijmolt, Van Heerde, and Pieters 2005). This shift from purely supply-side pricing to personalized pricing allows companies to optimize revenue, offer tailored recommendations, and adapt prices in real-time based on changing market conditions, creating a more efficient and customer-centric approach to pricing products and services. The idea of peak pricing (when firms charge customers extra fees during periods of high demand) is gaining acceptability in the marketplace. For example, peak pricing is implemented by utility companies, which charge higher rates during times of the year when demand is the highest (Burkhardt, Gillingham, and Kopalle 2023). Utility companies tend to charge higher rates in peak summer for higher electricity usage. The aim is to maintain the balance of demand and supply. Taxi companies and ride-sharing services also practice peak pricing or "surge pricing" to maximize profits. Uber's surge pricing is a prime example of this kind of tactic.

Dynamic pricing based on place

In the economics literature, many empirical studies have invalidated the law of one price: in reality, the prices of the same good can differ across different places or locations due to various reasons such as transport costs, trade barriers, and imperfect information that buyers have about prices in different locations (for a review, see Goldberg and Knetter 1997). Asplund and Friberg (2001) examine the law of one price in situations where none of the above reasons may apply. In their study, the lack of one price is due to different countries having different currencies. As an extreme case, the authors consider data from three Scandinavian duty-free outlets, where each product at the same location has price tags in at least two currencies, i.e., a customer has the option to choose between several prices for the same identical good. In such an extreme case of location-based pricing, the prices for the same good actually differ because the nominal prices are not continuously adjusted while exchange rates fluctuate daily.

Research in marketing shows the importance of changes in prices due to differences in locations. For example, Duan and Mela (2009) examine the issue of location-based dynamic pricing in the context of unobserved demand, where firms set prices conditional on their location and apply their model to over seven years of data on apartment location and prices. In other words, very similar apartments are being rented at different prices based on the location. Similarly, Albuquerque and Bronnenberg (2012) study the automobile market in the San Diego area and find that there is significant consumer disutility for travel. This results in automobile dealers having local areas of competition with a smaller set of competitors, which would enable dealers closer to market demand to charge higher prices than others who are farther away.

Li, Gordon, and Netzer (2018) acknowledge that geographically different prices for the same product would be beneficial for firm profitability. The authors also show that it is optimal for discount retailers to follow differential pricing in different local markets. In another context, Ngwe (2017) discusses outlet stores offering attractive prices at locations that are far from central shopping districts. The author argues that such dynamic pricing based on changes in locations forms an important component for firms' retailing strategies, particularly in the fashion industry. In order to counter brand dilution effects, the author shows that it is important for firms to prevent cannibalization of the main street stores with products sold in the outlet stores. In an interesting twist to the location of outlet stores, Bai, Gurnani, and Yin (2022) consider the case where retailers may feature an outlet-within-a-store concept and offer consumers the experience of outlet shopping at the same location. The authors show that such location-based pricing, i.e., outlet stores either co-located within the main store or at a remote location, depends on customer dispersion, customer-product fit, and customer travel sensitivity.

Ngwe, Ferreira, and Teixeira (2019) consider the case of online shopping contexts where customers can easily access regularly priced products that may be discounted at some online stores. The authors propose that deliberately increasing search friction by placing obstacles to locating discounted items can improve an online retailer's profitability. Such friction would allow sales of the same product at regular prices since consumers may not want to incur the search cost to locate that product at a discounted price.

Thus, based on extant literature, it is our thesis that even in the face of the future of shopping (Rigby 2011) where there is an abundance of information, near-perfect price transparency, and a plethora of special deals, location-based dynamic pricing is here to stay in both online and offline retail platforms.

Current challenges and future research directions in dynamic pricing

Dynamic pricing, the practice of adjusting product or service prices based on changes in four key dimensions: People, Products, Periods, and Places, and combining with factors such as competition, is transforming industries across the board. From the airline industry in the 1980s to the modern-day real estate market and retail stores, dynamic pricing has become a powerful tool for businesses to optimize revenue, improve profit, and enhance customer experiences. The application of machine learning and AI has further revolutionized dynamic pricing. Price adjustments are made using real-time data analytics, frequently assisted by AI and machine learning, in reaction to changes in customer demand, market conditions, and other external factors.

Implementing dynamic pricing relies heavily on the firm's data analysis capabilities. Building and maintaining pricing algorithms can be costly. Companies may need to invest in software development or purchase price optimization software. They need to invest not only in data collection, storage, and retrieval tools but also in hiring and training data managers who can collect, store, and retrieve data, and data scientists who can analyze and interpret the data. Customized algorithms may need ongoing maintenance and updates. Scalable and robust information technology infrastructure may be required to handle the data processing and real-time adjustments for dynamic pricing. This can involve significant upfront and ongoing costs, which may explain the paucity of dynamic pricing at grocery retailers (Nijs et al. 2007). Bradlow et al. (2017) discuss the case of an anonymous retail chain to assess whether the implementation of the new pricing strategy would lead to a significant increase in gross margin. Because the proposed price changes were beyond the range of the historical data, a field experiment compared results at 21 test stores compared to 21 control stores. First, the researchers had to carefully match the stores based on several variables, such as store size, consumer demographics, and yearly sales on 788 SKUs. Next, they estimated a logit-type, aggregate-based SKU-level attraction model (Cooper and Nakanishi 1988), followed by the price optimization algorithm. The results showed a weekly per store gross margin improvement of \$ 0.407 per SKU (around an average gross margin of about \$16.00), which would translate into about \$8M yearly gross margin improvement for the chain, about an increase of 2.5%. Of course, this increase may be assessed against the cost of implementing a price optimization system at the chain level, and potential backlash from consumers.

Importantly, fully automating the price-setting process is not standard practice. Most firms involve human intervention to review and approve algorithmic recommendations before implementing them in the market. Employees need to understand how dynamic pricing works and how to use the tools and systems effectively. Training programs and educational resources may be necessary. Ensuring that dynamic pricing practices are ethical and compliant with regulations, which may involve legal and compliance costs, including conducting pricing audits and assessments. Implementing dynamic pricing across an organization may require changes to existing systems and processes. Integration costs can vary depending on the complexity of the implementation. It is important to note that the costs associated with dynamic pricing can vary widely depending on the industry, the scale of operations, and the specific pricing strategies employed. While Bradlow et al. (2017) and Srinivasan et al. (2008) quantified revenue and profit benefits for dynamic pricing over time at grocery retailers, future research should aim to generalize these findings and compare them with dynamic pricing costs across industry, company size, and strategy.

Implementing dynamic pricing in practice requires various tools and techniques to estimate demand models. Consumer choice modeling and regression analysis are more powerful than econometric models to estimate demand models and price elasticities. Traditional time series forecasting models like moving averages, exponential smoothing, and ARIMA models continue to demonstrate their effectiveness in demand prediction. Additionally, emerging neural network-based models like RNN and LSTM are steadily gaining recognition in this domain. A notable example is "Prophet," an open-source forecasting tool developed by Facebook that is easy to use. Newer forecasting tools leverage these advanced machine learning tools to provide accurate demand forecasts.

Future research directions

Key insights that emerge from our findings on the importance of examining dynamic pricing via our "4 Ps" framework open the door to interesting research questions (Table 5). We organize the questions by each of our four key dimensions (People, Products, Periods, and Places) and the corresponding privacy and ethics issues, along with examples of empirical methods and data sources that could illuminate them. While the list of questions is not exhaustive, it illustrates how scholars may identify and examine new opportunities and strategies that may advance firms' understanding and dissemination of dynamic pricing and the corresponding implications for consumers and regulatory authorities. We discuss a few of these in more detail below.

People Q1 & Q2, Products Q3. Fully automated, machine-driven pricing constantly analyzes the data, forecasts demand,

Table 5
Examples of future research questions.

	Examples of research questions	Examples of empirical methods and data to utilize
People	1. How can stores sense changes in demand in real time and adjust prices accordingly, and what are the effects on consumer behavior?	Lab experiment, consumer survey, natural or field experiment with instances when prices are varied across segments.
	2. How do consumers perceive dynamic pricing on ESLs in physical stores with the dynamic pricing in online stores?	Lab experiment, consumer survey.
	3. What is the impact of information asymmetry between consumers and retailers in dynamic pricing and how can retailers build trust and mitigate customer dissatisfaction due to dynamic pricing?	Lab experiment Consumer survey Natural experiment with instances when incentives to customers are varied across segments.
Products	1. What new methodologies should be developed to improve the reinforcement of learning-driven dynamic pricing across various categories and departments?	Observational study, natural experiment, or field experiment, involving introduction of the focal product/ solution /technology.
	2. What factors influence firms to collaborate on pricing strategies across departments and when to compete in oligopolistic markets?	Lab experiment, consumer survey.
	3. What are the ways in which stores may leverage individual customer level basket data and provide personalized pricing and promotions across multiple categories and departments?	Secondary data (market basket data) from stores
Periods	1. How can reinforcement of learning-driven dynamic pricing adapt to situations of unexpected shifts in market trends and demand curves?	Lab experiment, consumer survey, field experiment featuring a campaign.
	2. In what ways may firms optimize exploration and exploitation while determining profit maximizing prices over a long period of time?	Simulations, field experiments.
Places	1. In what manner can multi-agent deep reinforcement learning models be applied to dynamic pricing in situations where businesses adjust prices simultaneously?	Lab experiment, consumer survey.
	2. By what method(s) can location-based pricing be used to enhance sustainability by promoting products in physical stores and online settings?	Lab experiment, consumer survey, field experiment involving distinct segments.
Privacy and Ethics	1. What is the impact of utilizing consumers' past data to determine dynamic pricing of products and services on consumer privacy concerns? What trade-offs can firms make i to balance the firm and consumer needs?	Secondary data (market basket data).
	2. What measures should be taken by policymakers in safeguarding consumer rights and privacy while allowing businesses to implement dynamic pricing?	Natural and field experiments.
	3. What are the ethical considerations for surge-type dynamic pricing, particularly during emergency contexts?	Consumer survey, lab experiment, conjoint study.
	4. How would consumers perceive pricing information when firms combine multiple types of dynamic pricing?	Lab experiment, consumer survey.

and adjusts prices to maximize revenues. While online retailers have been at the forefront of implementing dynamic pricing strategies, traditional brick-and-mortar retailers can also benefit from this practice. Dynamic pricing can help traditional retailers compete with online giants by offering unique value propositions and tailored experiences. Dynamic pricing can be adopted for physical stores by using electronic shelf labels (ESLs). These digital labels can be set up at any retail outlet and can help keep prices up to date on listed products. The introduction of ESLs has made it easy for retailers to implement dynamic pricing and level the playing field with E-commerce vendors. ESL creates synergies between dynamic pricing engines, price displays, and point-of-sale systems.

Products Q1, Periods Q1 and Q2, Places Q1. Dynamic pricing requires a balance between exploring new price points and using existing pricing rules and heuristics. Managing the difficulties of shifting demand and price optimization is made easier by A/B testing and multi-armed bandit algorithms like Thompson Sampling, a statistical technique that balances the investigation of various pricing strategies with the utilization of established pricing structures. This approach can help organizations over time get closer to the "real" best price, even when demand is affected by a variety of changing factors. In addition, deep learning algorithms, with their ability to process large datasets and understand complex relationships, are enabling businesses to move beyond traditional supply-side pricing to personalized pricing. For example, by analyzing customer attributes and preferences, machine learning can predict price outcomes within addressable markets and time constraints, matching properties with highly probable buyers or renters in real estate markets. Another growing area is dynamic pricing on e-commerce platforms using reinforcement learning algorithms. For example, in a 2019 field experiment using a reinforcement learning model during a markdown season, Liu et al. (2018) concluded that the Deep Q networks model performed much better than manual markdown policies, achieving a higher total profit.

Products Q2. Overall, the future of pricing is dynamic, with artificial intelligence (AI)-driven algorithms enabling businesses to optimize pricing strategies, enhance efficiency, and provide personalized experiences to customers across various industries. As technology continues to advance, the potential for dynamic pricing to reshape the economy and customer behavior is vast. Yet there are potential pitfalls. For example, while machine learning and AI are beneficial for real-time price adjustments, recent research highlights the potential for these algorithms to overlook external factors such as competitor prices, leading to long-term monopolistic pricing and inadvertent collusion (Hansen et al. 2021). Researchers found that independent AI pricing algorithms can result in pricing outcomes that are not in sync with the marketplace. They demonstrate that independent algorithms can drive prices above competitive levels as they may not have considered competitors' prices. This reveals the need for firms to strike a balance, considering factors beyond an algorithm's scope, competing where necessary and preventing unintentional monopolistic pricing dynamics. Sometimes, through automation, firms may use AI to collude on prices or charge supra-competitive prices without communicating with each other (Calvano et al. 2020). The risks involved in allowing AI to control prices may trigger price wars among firms, with negative consequences across market players (Van Heerde et al. 2008). Thus, humans should continue to have oversight on dynamic pricing.

People Q3 and Place Q2. Some studies highlight the long-term effect of dynamic pricing on firm profitability, brand loyalty, and customer satisfaction. For example, Bradlow et al. (2017), Nijs et al. (2007), and Srinivasan et al. (2009), show that dynamic pricing is associated with higher profits than price inertia in categories for the retailer. A recent study by Zhang et al. (2020) highlights that although price promotions increase short-term profits and customer engagement, influencing product views and purchases, they can also lead to unintended consequences over the long term. Other studies examine the long-term profitability of price promotions and discuss how dynamic pricing affects customer welfare (e.g., Srinivasan et al. 2004; Chen and Gallego 2019). Overall, extant research shows that dynamic pricing affects customer satisfaction.

Privacy and Ethics Q1, Q2, Q3, and Q4. Consumer reaction to dynamic pricing remains an important research area. On the one hand, automation can enhance the efficiency, accuracy, and scalability of dynamic pricing and provide short term elasticity to justify real-time pricing. However, automation also influences consumers' psychological responses to dynamic pricing, including their perceptions of control, fairness, and value. Fairness is a context-dependent and subjective concept that reflects the extent to which consumers evaluate a price to be reasonable, acceptable, or justifiable (Haws and Bearden 2006). Perceptions of fairness can influence customer satisfaction, loyalty, trust, word-of-mouth, and intention to purchase (Selove 2019). Dynamic pricing can pose significant challenges and risks for businesses, as it may elicit negative responses from customers who view it as unjust or discriminatory. Therefore, it is essential for businesses to comprehend how consumers perceive and react to dynamic pricing in order to design and implement effective pricing strategies. For example, Whitney Houston's albums became more expensive after she passed away. Algorithms correctly identified the higher demand, and thus increased the price. However, customers perceived this as tasteless, and Sony had to apologize to them[1] The use of technologies such as facial recognition to identify customer emotions and demographics to offer personalized prices may infringe on consumers' privacy rights and expose them to manipulation and discrimination. For example, home automation technology can diminish consumers' sense of control over their energy consumption, making them feel less accountable or involved (Bollinger and Hartmann 2020). Martin et. al. (2020) discuss the data privacy issues in retail and highlight the complex interrelationship among consumers, retailers, and regulatory forces.

Although algorithms provide a fast and cost-effective way to detect demand-supply changes and adjust prices accordingly, they may miss important human considerations. For perishable products, algorithms are likely less able to gauge product quality than are people, who use all their senses to do so. In such cases, if there is a lack of human intervention, it would hurt the firm's reputation and customer trust[2] Price cannot be reduced to a mere economic dimension when humans are decision makers. Indeed, customer perception and reaction are key, and require further inquiry.

While dynamic pricing aids in balancing supply and demand in ride-sharing and food delivery services, it might result in unhappy customers during price increases. Businesses need to consider ethical implications, transparency, and customer perceptions to avoid negative impacts. Nunan and Di Domenico (2022) present governance mechanisms that help firms address ethical concerns while implementing algorithmic pricing. Dynamic pricing creates ethical issues, particularly in emergency situations where customers and journalists may describe it as predatory. For instance, surge pricing might increase profits during times of high demand, but can also be seen as price gouging, especially in times of catastrophes or natural disasters. Regulatory oversight may address such unethical behaviors, but firms are well advised to preemptively reflect on what "the right thing to do" means in such circumstances.

Conclusion

In this paper, we (1) offer a working definition of dynamic pricing, (2) detail four key dimensions that underlie dynamic pricing, and (3) propose areas of interest to managers and scholars moving forward. In the future, dynamic pricing is expected to become even more prevalent. While dynamic pricing is clearly a powerful tool for increasing firms' revenue and profit, it also raises ethical and practical concerns that need careful management and, maybe, governmental guidance. Therefore, companies that consider using this strategy must balance the potential for higher returns with the possibility of a detrimental impact on customer relationships and, more broadly, society. From our perspective, it is exactly this delicate tradeoff, mixed with the increasingly managerial

[1] https://www.businessinsider.com/sony-tried-exploiting-whitney-houstons-death-with-an-album-price-hike-2012-2.

[2] https://www.simon-kucher.com/en/insights/8-dos-and-donts-dynamic-pricing.

relevance of an instrument that is ultimately highly technical in both conceptualization and deployment, that makes the study of dynamic pricing a perfect case for collaboration between marketing practice and marketing science. It is unlikely that marketing professionals can advance wisely in the development of dynamic pricing tools without the partnership of marketing scholars with state-of-the-art methodological skill sets. Similarly, it is unlikely that marketing scholars can generate insights that are truly important and relevant without the partnership of marketing professionals that spell out and reinforce the many nuances that cannot be escaped in real-life settings. Thus, while work remains to be done, the concept of dynamic pricing seems viable and worthy of the effort required to more fully understand it.

Declaration of Competing Interest

None.

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