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Algorithmic Pricing in the digital age

“Ethical considerations on its economic and social implications, and an analysis of possible solutions to overcome its critical issues”

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Abstract

Algorithmic pricing is an emerging business practice that uses computational algorithms to determine the prices of products and services based on a number of dynamic factors. The aim of this thesis is to draw attention to the existence of these business practices, and the ethical and social implications that derive from them, and then focus on what could be effective solutions to increase the well-being of the community.

In Chapter 2 of the thesis, a general introduction to the topic will be made, starting from its history and its evolution over the years; Chapter 3 will examine the different types of pricing algorithms. Subsequently, in Chapter 4 we will analyze the sectors in which they are most applicable, and the relative advantages and disadvantages they bring with them, with a critical analysis of the trade-offs generated. The effect of algorithmic pricing on competition will be studied, considering how the ability of algorithms to adapt quickly to market conditions can foster anti-competitive practices, such as price discrimination. Later, in Chapter 5, we will look at the issue of price transparency and how the opacity of algorithms can make it difficult for consumers to understand the pricing process and assess whether they are receiving fair treatment.

To address these ethical issues, several possible solutions will be brought to light, described in Chapter 6, which will focus on the role of the government, as a regulatory, of the end consumer, who must be encouraged to educate and inform himself about the use of these practices, and of the company, as responsible for making its customers aware and acting in compliance with government laws, for fair and non-discriminatory use.

1. Introduction

In the digital age we live in, the use of algorithms has permeated every aspect of our lives, including how rates are set for the products and services we purchase. Algorithmic pricing is one of the most significant phenomena in the contemporary commerce landscape. This practice, based on the use of complex algorithms, aims to determine prices dynamically and adaptively, considering a wide range of variables and market conditions in real time.

Algorithmic pricing is not a new concept, but rather an evolution of pricing strategies adopted throughout the history of commerce. Since the early days of modern commerce, merchants have sought to maximize their profits by adjusting prices based on supply and demand. In the pre-computer era, the price was adjusted manually, and this led to a very high expenditure of time and costs; keeping track of prices and those of rival companies became increasingly difficult. However, with the advent of digital technologies and access to huge amounts of data, algorithms have become indispensable tools for optimizing this practice, and the first sector that became part of it was transportation, and in particular airlines.

There are different types of algorithms used in algorithmic pricing, each with its own peculiarities and applications. From machine learning models that learn from historical data to predict consumer behaviors, to rule-based algorithms that dynamically respond to real-time market conditions. Nowadays, with the advent and integration of artificial intelligence, these tools have become even more sophisticated and performant.

Algorithmic pricing has found application in a wide range of industries, ranging from e-commerce to tariff management in transport, from energy distribution to the financial sector, up to healthcare (for the determination of hospital tickets). This diffusion testifies to the effectiveness of such strategies in optimizing profits and improving the operational efficiency of companies.

There are many typologies of algorithmic pricing, but two of them differ in the way they operate and the wide diffusion they have encountered in recent years; the first, dynamic pricing, considers more economic factors, such as supply and demand, competitor prices, and for this reason has a more economic impact. The second, personalized pricing, aims to categorize consumers and create a market and customer segmentation, through the analysis of their preferences, behaviors, and other factors; for these reasons, the latter certainly has a stronger impact from an ethical and social point of view.

The indiscriminate use of algorithms in pricing raises several moral concerns because there is a risk that such practices lead to discrimination against certain groups of consumers, amplifying existing inequalities in society. In addition, a lack of transparency in algorithmic decision-making processes can undermine consumer trust and undermine their freedom of choice.

Since discussions about the ethics of algorithms in general and algorithmic pricing in particular are still limited, in the final part of the thesis, we will focus on identifying effective solutions to address these issues and promote community well-being. These solutions could include implementing stricter regulations on the use of algorithms in pricing, promoting transparency and accountability by companies, as well as developing new business models that put ethical and social values at the center. Through critical analysis and the identification of innovative solutions, it aims to contribute to the ongoing debate on how to reconcile economic efficiency with respect for ethical principles and consumer rights.

2. Background of Algorithmic Pricing

The first chapter of the thesis will focus on the general analysis of the topic of algorithmic pricing, starting first of all from its history and the evolution it has had over the years, and then getting to describe what are the fundamental concepts and the main types used, and a detailed analysis of the impact that this pricing strategy has had in the main sectors, from e-commerce to finance.

2.1 History and Evolution of algorithmic pricing

Algorithmic pricing, which uses sophisticated computational techniques to dynamically set and adjust prices, represents a paradigm shift in pricing strategies. Since dynamic pricing is a pricing strategy based on mathematical models and economic principles that have been developed over time, it cannot be attributed to a single inventor. The theory of price discrimination, which was researched in the 19th and 20th centuries by economists like Arthur Cecil Pigou and John Stuart Mill, is the foundation for the concept of dynamic pricing. Price discrimination represents the practice of offering the same product to different customers at different prices depending on their willingness to pay.

Pre-computer era and emergences of computer

Historically, most pricing has been dynamic, with customers negotiating with merchants to obtain the best deal on a product. The price may differ significantly because retailers may decide to immediately raise the price if there is a high demand for the product and a limited supply. In contrast, a store owner could lower the price to boost sales volume if they wanted to get rid of an extra item. Retailers also had the option to alter their prices based on the customer. The retailer would set the price higher when a customer appeared to have more money than when they appeared to have less. In short, in this pre-computer era, businesses relied on basic pricing models, manually adjusting prices in response to factors such as production costs, supply, demand, and competition.

However, this system was, to put it mildly, ineffective. As businesses expanded during the Industrial Revolution, keeping track of prices became increasingly difficult and time-consuming, and the system proved to be unscalable. Retailers had to devise a fresh strategy for handling their pricing... and they came to look at the price tag.

The price tag, which was developed in the 1870s, relieved store owners of the burden of remembering the cost of every item in the store and allowed companies to offer more intricate assortments at higher prices. Also, it has sped up and improved equity for all checkout processes. Retailers only needed to determine the price of a product once and then apply it to the price tag on the product inside the store.

Price tags are still important today, at least in the eyes of the buyer. Price remains the most significant "P" for most consumers, and many are content to purchase a product from any retailer as long as the price is right. Furthermore, they continue to have a function in terms of scalability.

That does not, however, imply that the cost is static, both literally and metaphorically. Retail is evolving due to e-commerce and new technologies, and paper price tags are quickly going out of style. The way we buy, and sell has changed due to modern technology, which has also made price fluctuations more frequent.

Dynamic pricing in Airlines

The first sector to switch from a fully labeled world to one where prices fluctuate daily and weekly was the airline industry. The US government strictly regulated airline prices before the 1980s. But that changed during the 1980s, when the industry took over price-fixing and it saw the integration of computers into business operations, prompting a shift toward more sophisticated pricing strategies.

Those were the days when manual price adjustments were made on the computer by ex-ticket clerks. The cost of a seat varied according to several factors, such as the time of day the flight, the proximity to the departure, the duration of the flight, and more; however, the clerk ultimately determined the price based on their "gut feeling." The system was incredibly inefficient, resulting in significant financial losses for the airlines.

However, the airlines soon discovered that these modifications were being made by computers.... computers that could automatically adjust the price of a seat based not just on intuition but also on knowledge of the flight path.

Airlines decided to take the risk and invested millions of dollars in software to automatically update ticket prices based on a variety of factors, just like many retailers do today. By introducing this new "yield management system", which would later be the precursor of algorithmic pricing, airlines were able to optimize revenues by dynamically adjusting ticket prices. The term "dynamic pricing" refers to this kind of pricing that has assisted numerous businesses in overcoming financial difficulties. The rest of the travel industry, including cruise lines and hotel chains, quickly followed suit after this achievement.

E-commerce and online retail

The introduction of the internet in the 1990s brought about a radical change in the way we work and live. Businesses made investments in new technology that would enable them to transmit and receive electronic business and personal communication; these technologies, known as "e-commerce.", provided new opportunities for algorithmic pricing. In an attempt to fulfill these new demands for e-commerce, a number of new businesses emerged; however, when the dot-com bubble burst in 2000, these businesses failed.

But in 2000, the definition of "e-commerce" changed referring therefore to the ability to purchase anything online. And retailers were aware of the clear advantages of an internet marketplace, and they started utilizing algorithms to dynamically adjust prices based on multiple factors. Retailers has the opportunity now to reach a whole new market by extending their assortments beyond their physical store. Additionally, consumers have rapidly gotten used to the convenience of online shopping.

Amazon and eBay were the first two companies to truly push this electronic marketplace idea to a whole new level. Every business has discovered incredibly creative methods to capture the power of the internet for retail. To promote its products further, Amazon, for instance, developed an affiliate marketing network and the Prime membership program.

With the growth of e-commerce, software technology also changed. In a sense, price tags have regained significance due to e-commerce, even if in a completely different way. In many cases, price is now the only factor that matters to customers in the flattening e-commerce market. The market price of a product fluctuates multiple times a day as a result, and retailers now find it difficult to maintain competitive prices at all times.

So, this puts retailers in a hard situation. Retailers are currently updating their prices by hand, just like airlines used to do. To comprehend the market for each product in their assortment, entire pricing teams devote two to three hours a day to simply monitoring the prices of competitors. In order for these pricing teams to remain competitive, they must then update their online stores and determine new prices in accordance with their company's strategy. Then, in order to continue being relevant, they must restart this process from scratch.

The speed at which e-commerce is developing has an impact on physical stores as well. Without the right technology, retailers can easily charge two completely different prices for the same product depending on whether it is bought online or in person.

Without the aid of technology, retailers are essentially unable to compete in the new market. Handling prices manually takes a lot of time, money, energy, and effort. It remains ineffective even now. Too many options are available, and prices are changing too quickly for us to keep up with them, and it is for these reasons and in this way that the use of dynamic pricing software becomes necessary.

Dynamic Pricing in today's retail environment

It's unlikely that we'll go back to a time when negotiating over prices with store owners is common, we are headed toward a time when computers, via dynamic pricing software, set the prices. Like airlines in the past, a growing number of retailers are realizing that managing their pricing can be done more simply and effectively, and they are investing the necessary funds in software technology. Retailers may devote time and resources to developing their own dynamic pricing strategy, but occasionally they contract out the task to a third party. Just to mention, Amazon and Uber are examples of companies that have developed and used their own dynamic pricing strategy in these last years, but for most businesses, it is usual to rely on a third-party software company.

From mid 2010s to present, algorithmic pricing evolved into personalized pricing, tailoring prices to individual consumers based on their browsing history, purchase patterns, and other behavioral data; this phenomenon has attracted the attention of regulators and antitrust authorities regarding the limit between use and abuse of these systems, fairness, transparency, and protection of customer personal data and all the aspects related to the ethicality and morality of this business practices.

Enabled by continuous advancements in computing power and algorithmic complexity, this digital ecosystem is itself exemplary of a new type of data capitalism. In this environment driven by 'big data,' companies have to act and respond quickly to constantly changing market conditions, adjusting their strategies based on available information and industry have implemented algorithmic pricing approaches. Moreover, with the advent of artificial intelligence, these automated systems are becoming increasingly high-performance, complex and so very difficult to understand from the outside. With technology firms such as Google, Microsoft, and Amazon, offering algorithmic pricing solutions out of the box, there are no obstacles for the widespread use of the pricing strategy, even for smaller sized companies. (Seele, P. et al., 2021)

To summarize, algorithmic pricing is a dynamic and changing field these days, with companies constantly adjusting and improving their approaches to remain competitive in a market that is becoming more and more data-driven and technologically sophisticated.

Algorithmic pricing therefore benefits substantially from the development of a whole new ecosystem, entailing rapidly advancing information and communication technologies and e-commerce systems. (Seele, P. et al., 2021)

The history of algorithmic pricing shows a persistent attempt to use technology to make more effective and efficient pricing decisions, but this progress has been hampered by the need to deal with moral and legal issues. As we explore applications, impacts, and ethical considerations in subsequent chapters, this historical foundation provides context for understanding the complexity of algorithmic pricing.

2.2 Fundamentals of algorithmic pricing

The understanding of algorithmic pricing begins with the nature of price and pricing. Price – which represents the term of an exchange - is a key feature of markets. Setting prices is a crucial choice that affects how much money buyers and sellers make from their transactions in a market. Therefore, it should come as no surprise that research on pricing and pricing strategies has been done in a variety of economic and business study fields. Even though the majority of the approaches have a foundation and element oriented toward economics, they can differ from each other in a number of ways depending on the goals and methodologies used. Thus, if one were to study the applications of new technologies to pricing—such as algorithmic pricing—it would be useful to examine the nature of the diversity in pricing strategies (and methodologies) and their implications in a new pricing-technology environment. (Seele, P. et al, 2021)

Once we have introduced and explained what price and pricing are, it is important to be able to give the most precise definition possible to the concept of algorithmic pricing; personally, among the many definitions existing on the web and that I have analyzed, I believe the most accurate is the following one:

Algorithmic pricing is a pricing mechanism, based on data analytics, which allows firms to automatically generate dynamic and customer-specific prices in real-time. Algorithmic pricing can go along with different forms of price discrimination (in both a technical and moral sense) between individuals and/or groups. As such, it may be perceived as unethical by consumers and the public, which in turn can adversely affect the firm. (Seele, P. et al, 2021, p.704)

This definition is a refined and ethically informed version of Cormen's 2009 proposal, which stated that “Algorithmic pricing is a pricing strategy that builds on computer algorithms, which set prices for goods and services dynamically at either the aggregate or individual level.”¹ Algorithms, broadly defined as “a sequence of computational steps that transform the input into the output,”¹ are automated tools that solve previously specified problems.

Regarding the different types of existing algorithmic pricing, in this thesis we will focus only on the two main ones, which are dynamic and personalized pricing. Dynamic pricing is the practice of changing the prices of products and services in response to changing market conditions and/or increased access to market information (such as demand and supply). The study of dynamic pricing covers a number of overlapping areas, including economics, marketing, and revenue management. Sales promotion and markdown are two common forms of dynamic pricing that have received extensive research. Sales promotions include temporary price reductions within a specific timeframe. Markdown pricing involves lowering the prices of goods that are either perishable (e.g., food) or have lower values after a given season (e.g., fashion items). (Seele, P. et al, 2021)

Personalized pricing can be seen as a first-degree price discrimination, and it’s also known as targeted or customized pricing and consists of a pricing strategy in which firms charge different prices to different consumers based on their willingness to pay. (Seele, P. et al, 2021)

Again, according to a study conducted by Rott, P. et al for the Policy Department for Economic, Scientific and Quality of Life Policies of European Parliament, personalized pricing can be described as “price differentiation for identical products or services at the same time based on information a trader holds about a potential customer”. (Rott, P. et al, 2022).

It has become possible because traders have obtained personal data, either legally or illegally, which they, or rather the algorithms they use, can process to understand individuals' personal preferences and purchasing habits. Personalized pricing enables traders to capitalize on their customers' (inferred) willingness to pay more, thereby increasing their profits.

If we want to better understand how these automated pricing systems work, it is important to look at some features and capabilities. It is now established that algorithmic pricing use rule-based or self-learning algorithms to automatize decision-making in price management. In most retail and consumer goods applications, this generic concept typically translates into some combination of the following characteristics:

¹ Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). Introduction to algorithms (3rd ed.). Cambridge: MIT Press

- **Dynamic pricing:** automated decision-making allows for more frequent and precise changes to various components of the price waterfall, such as base prices, promotions, and special offers. These changes help pricing accommodate competitor moves, inventory turnover, clearance goals, and demand spikes in a profit-maximizing manner.
- **Personalization:** the algorithmic approach aids in the segmentation and personalization of specific price waterfall elements, such as discounts and special offers. It also accounts for variations in consumer preferences, price sensitivity, and other statistical data on potential buyers.
- **Developed differentiated pricing strategies:** data-driven methods can help optimize pricing strategies for various products and categories based on the product's impact on consumer value perception, similarity to other products, and other factors.
- **Optimality guarantees.** The data-driven approach aids in determining near-optimal pricing parameters and identifying missed opportunities. For example, an algorithmic promotion management system can recommend new promotions to improve the performance of the baseline promotion calendar.
- **Advanced internal and external signals:** algorithmic pricing frequently relies on statistical analysis of transactional, inventory, and catalog data, as well as external signals like competitor pricing, to improve decision quality and respond to trends. In some cases, it employs natural language processing (NLP) and image recognition technologies to extract textual and visual information, such as product descriptions and images.
- **Integration with merchandising and inventory management:** algorithmic pricing uses stock level and selling velocity data to optimize prices and prevent stockouts and overstocks. On the other hand, the fundamental capabilities required for algorithmic pricing, such as demand modeling, are frequently used in other use cases, such as assortment and inventory optimization.

These features and capabilities can be implemented and used differently depending on strategic considerations and other factors. In other words, algorithmic pricing is not a pricing strategy but rather a toolkit for executing a pricing strategy efficiently.²

² <https://medium.com/codex/algorithmic-pricing-part-i-the-risks-and-opportunities-d7ae8a9e9484>

2.2.1 Artificial Intelligence impact on algorithmic pricing

Artificial intelligence (AI) is revolutionizing numerous economic sectors, including pricing, through the implementation of advanced algorithms and data analysis. It's not always evident how artificial intelligence technologies affect price management procedures. For instance, price elasticity analysis frequently employs simple machine learning techniques, and the benefits of these approaches are widely recognized.

In business operations, more sophisticated and cutting-edge techniques like reinforcement learning, picture categorization, and natural language processing are employed less frequently. Their use in pricing management is less evident. This brief section will explore the impact of AI on algorithmic pricing and its effects on consumers and the market.

Implementation of Artificial Intelligence in Pricing

The use of AI in pricing has allowed for the development of complex algorithms that are capable of analyzing vast volumes of data and forecasting the best prices under various conditions. For instance, to find the most advantageous rates and optimize earnings, machine learning algorithms might examine past sales data, market trends, and consumer behavior.

According to a study conducted by McKinsey & Company, the use of AI in pricing can lead to an increase in revenues of up to 5% and a reduction in operating costs of up to 15%, highlighting the potential positive impact of this technology on business performance.

Effects on the Market Ecosystem

The implementation of AI-powered algorithmic pricing can affect market balance and competitive dynamics. While it can foster price transparency and market efficiency, it could also lead to discriminatory or anti-competitive pricing practices.

Based on a study conducted by Harvard University, algorithmic pricing can lead to "price steering" or "algorithmic collusion," in which companies use algorithms to coordinate their prices and limit competition, thus violating antitrust laws.

Impact on Consumers

The adoption of AI in algorithmic pricing can have a significant impact on consumers. While it can allow them to access more competitive and personalized pricing, it could also lead to increased price discrimination and loss of transparency.

The U.S. Federal Trade Commission (FTC) found that algorithmic pricing can lead to increased price segmentation based on consumer profile, resulting in increased price discrimination against certain groups.

The implementation of Artificial Intelligence in algorithmic pricing has the potential to fundamentally transform the way prices are determined in global markets. However, it is important to carefully consider the social and economic impacts of this technology, in order to ensure a balance between economic efficiency, fair competition, and consumer protection.

2.3 Applications of algorithmic pricing in different sectors

Because algorithmic pricing can adjust in real time to changing market conditions, it is widely used in many different industries. This section examines the application of algorithmic pricing across various industries, demonstrating its adaptability and influence on pricing tactics.

2.3.1 Retail and E-commerce

The world of e-commerce and retail has completely changed as a result of algorithmic pricing, which gives companies data-driven, flexible approaches to optimize pricing choices. Dynamic pricing concepts can be combined with advanced e-commerce strategies to continuously maximize profit margins in real time. However, a word of caution is in order: if not executed properly, dynamic pricing can reduce conversions as buyers realize your prices are always changing. It can undermine trust in general, and if customers are aware that prices may be dropping, they are more likely to wait it out.³

This section examines the various uses of algorithmic pricing in e-commerce and retail, highlighting how it affects customer experiences, pricing strategies, and general market dynamics.

Algorithmic pricing enables retailers to implement personalized pricing strategies, tailoring product prices based on individual customer data. This approach considers factors like browsing history, purchase patterns, and demographic information. Dynamic pricing algorithms analyze also market conditions, competitor prices, and other relevant data in real-time. This allows retailers to adjust prices dynamically, responding to changes in demand, supply, and other external factors.

Algorithmic pricing tools constantly monitor and analyze competitor prices, providing retailers with valuable insights. This competitive pricing intelligence helps businesses stay agile and adjust their prices to remain competitive in the market. Another function exploited by retailers is leverage

³ <https://www.vaimo.com/blog/ecommerce-pricing-strategies-essential-guide/>

algorithmic pricing for price optimization, determining the most effective pricing strategy to maximize revenue. This involves analyzing historical data, customer behavior, and market trends.

Furthermore, algorithmic pricing helps retailers manage inventory effectively by implementing clearance pricing strategies. By analyzing factors like stock levels and product shelf life, algorithms optimize prices to clear excess inventory. Again, e-commerce platforms employ algorithmic pricing to strategize flash sales and limited time offers. Algorithms consider factors like user behavior, demand patterns, and historical sales data to set optimal promotional prices.

Algorithmic pricing is used also to design and optimize loyalty program pricing. By analyzing customer spending patterns and preferences, algorithms recommend personalized discounts and rewards, enhancing the overall shopping experience. This personalized approach builds customer loyalty and encourages repeat purchases.

It can be concluded with certainty that e-commerce sector is the one most characterized by price algorithms; this type of price strategy has many more uses than just setting prices; it gives companies the ability to adjust to changing market conditions, maximize profits, and give customers individualized experiences.

2.3.1.1 Focus on Amazon dynamic pricing model

Let's try to understand better how Amazon dynamic pricing model works looking at the example reported in the image below (Figure 1), taken by the Wall Street Journal.

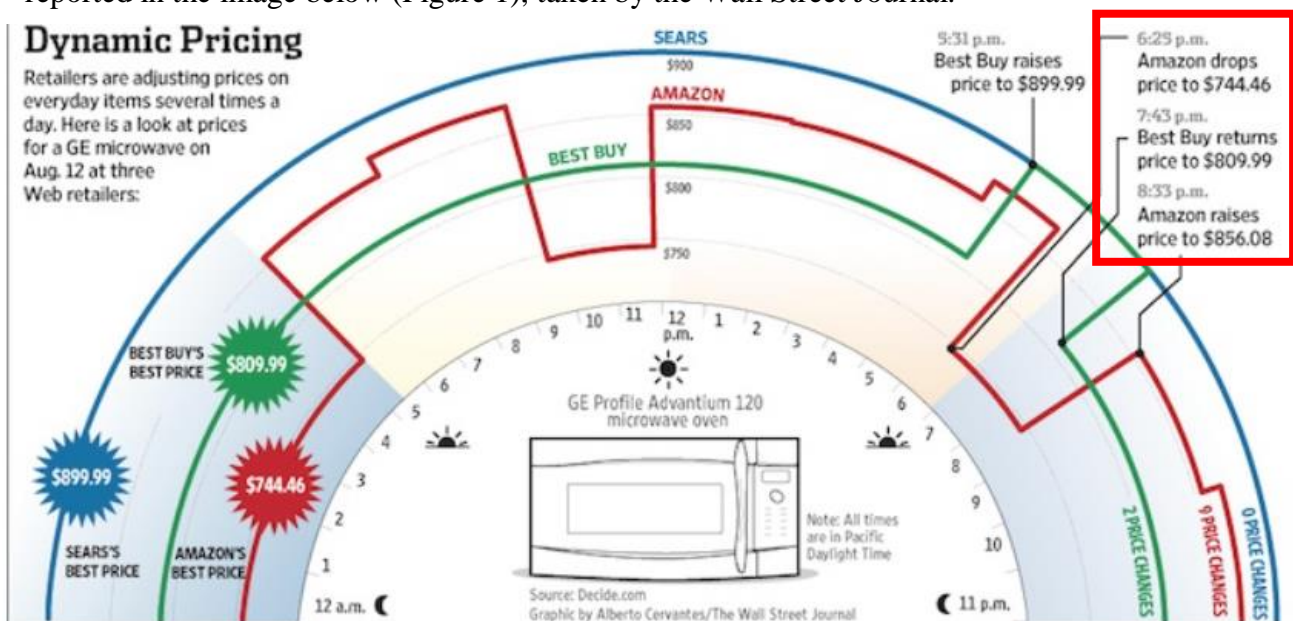


Figure 1

Source: Wall Street Journal. Available at: <https://econlife.com/2014/12/amazons-dynamic-pricing-power/>

The three retailers involved, in this case in the sale of a microwave, adopt three different pricing strategies. Sears imposes a constant price throughout the day, without making any price changes; Best Buy, on the other hand, maintains a fixed price until 5:30 p.m., and then increases it and reaches the Sears price level (\$900); after 2 hours, the price drops again to return to the initial level. Most likely, this variation is justified by the fact that in that time slot (17:30-19:30) consumers are more likely to buy online, since it is an after-work time, in which they have the freedom and the possibility to connect and search the web, and it is logical to think that there are therefore more users on the net.

Amazon, on the other hand, records 9 price changes during the day, which makes it really very dynamic; at night, the price is decidedly low compared to other retailers, as it is unlikely that a potential buyer will actually be connected online. Suddenly, from 5 a.m. to 9 a.m., the price recorded two price increases, then returned to the initial level between 9:30 and 12 a.m., and rose again from 12 p.m. to 6 p.m. Finally, from 6 pm to 9 pm the price drops again, and increases from 9 pm to midnight. In my opinion, these constant price changes are closely related to people's ability to get online and become potential buyers. Significant of this concept is the price increase of \$100 (from \$750 to \$850) in the evening time slot, when people are normally at home, not working and therefore have the opportunity to buy products online.

In addition, Amazon's dynamic pricing model analyzes the behavior of the other two retailers involved; as you can see, its price, despite recording multiple increases throughout the day, always remains below that of Sears, positioning itself on a super competitive level, and in the only moment when the price of Best Buy increases, that of Amazon decreases, and vice versa. This is a simple illustration of how Amazon's dynamic pricing model works, taking into account several factors to adjust and define a price that is always competitive and attractive to buyers.

2.3.2 Airlines

In the airline sector, algorithmic pricing has become indispensable, revolutionizing conventional pricing models and enhancing revenue management strategies. Particularly, dynamic pricing has become a crucial tool for airline companies, especially the low-cost ones such as Easyjet, Ryanair and Wizzair; the final goal is optimizing revenue and meet customer demands, and the way in which they achieve this represents one of the most customized and hidden yet fascinating processes in the market. It's clear that airlines operate in a highly dynamic and competitive environment, where factors such as passenger demand, fuel costs, and global economic variables can change rapidly. In this context, algorithmic pricing has proven to be a fundamental resource for optimizing pricing strategies, improving profitability and remaining competitive in the market.

The airline industry is characterized by highly variable demand and influenced by seasonal factors, special events, weather conditions, and geopolitical situations. Algorithmic pricing adapts to these changes, allowing airlines to adjust prices in real-time to maximize revenue. Large volumes of data, such as booking histories, industry trends, and rivalry patterns, are analyzed by pricing algorithms. With the use of predictive analytics, airlines are able to project demand and modify prices appropriately. For instance, prices might go up when demand is strong, and discounts or promotions might be available when demand is low.

Algorithmic pricing allows also the creation of dynamic rates, adaptable in real time. Airlines have the potential to employ tactics like differentiating prices according to factors including reservation time, duration of stay, seat availability, and service class. As a result, the value that travelers perceive is reflected more accurately.

Algorithmic pricing also allows airlines to rapidly modify their pricing strategy in response to changes in the external market. For instance, the system can detect and react instantly to preserve competitiveness if a rival abruptly drops pricing on a comparable route; this is a crucial aspect that must be considered and on which I would like to make a brief personal reflection. Algorithms can identify literally everything, and it seems that they don't leave room for errors or flaws, and the impression is that there is no limit to their depth of analysis.

Reaching this point, we have understood that algorithmic pricing is a key strategic lever for airlines, enabling them to successfully navigate a complex and changing market and optimizing overall profitability (first goal). Using advanced algorithms, airlines can achieve greater agility and accuracy in price management, ensuring a competitive position in the commercial aviation landscape.

2.3.2.1 Focus on Ryanair dynamic pricing model

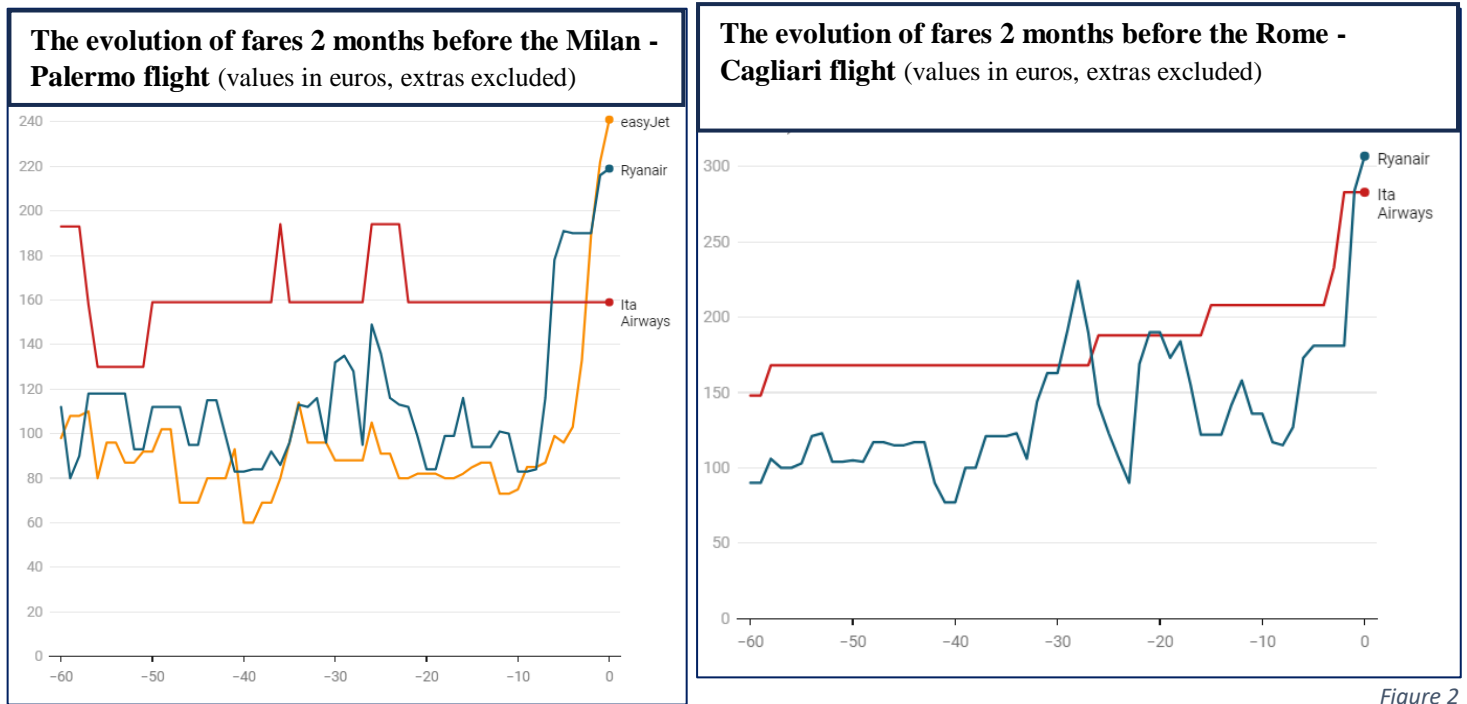


Figure 2

Source: Corriere della Sera. Available at: https://www.corriere.it/economia/consumi/23_agosto_11/caro-voli-come-funziona-l-algoritmo-biglietti-aerei-tariffe-diverse-ogni-giorno-140bb5a8-3828-11ee-aeb3-95a71d27ff6c.shtml

Recently, the algorithmic pricing model adopted by Ryanair has come under the magnifying glass of the Italian government, accused of carrying out discriminatory anti-competitive pricing policies.

Above in Figure 2 there are two examples useful for understanding the fluctuation of prices and their evolution over time on the Milan-Palermo and Rome-Cagliari routes of August 12th, 2023, taken by an article of Corriere della Sera.

Let's focus on EasyJet's and Ryanair's price curves and try to understand their trend; they clearly show the existence of dynamic pricing because they vary from day to day. In fact, 60 days before departure, prices remain decidedly lower and in a relatively constant, albeit very fluctuating, range; this is due to the fact that the algorithm, due to its way of reasoning, changes the price by as little as €1 in order to entice the passenger to book and, often, also to appear higher in search engines so as to be noticed more. As you get closer to the day of departure, the prices skyrocket, surpassing all the competition, reaching crazy figures. In the second chart, a month after departure, we can see how the price of Ryanair rises dramatically by more than double, and then suffers a rapid decline towards the initial price level; this fact could be due to a massive purchase by a group of people, for example for the presence of a Serie A football match, to which the algorithm adapts by immediately increasing prices. Why the curve drops shortly after? Because the same algorithm realized that in the following

hours there were no or almost no bookings, and so it had to reduce the fare to a figure deemed more reasonable, to support demand and fill the plane more satisfactorily.

2.3.3 Hotel Industry

The hospitality industry's pricing strategies have changed significantly in recent years due to the market's rapid evolution. Traditional pricing strategies, such as seasonal or fixed prices, were commonplace in the past. Nevertheless, these approaches proved inadequate to handle the varying market conditions and demand, which prompted the creation of contemporary dynamic pricing strategies.

In the hospitality industry, dynamic pricing has gained popularity because it enables businesses to modify prices in real-time in response to various factors such as price volatility, rivalry, customer behavior and external factors; all this contributes to determine the optimal price, revenue optimization, satisfy market demands, costs and profits, traditional and modern methods, internet accessibility, and the complexity of data inclusion.

This in-depth analysis explores the multifaceted ways in which algorithmic pricing is employed in the hotel industry, drawing insights from research studies and industry practices.

Algorithmic pricing enables hotels to make real-time adjustments to room rates based on a myriad of factors such as current occupancy levels, seasonal demand fluctuations, local events, and competitor pricing.

Algorithms analyze individual guest data, such as booking history, preferences, and loyalty program participation, to personalize room prices. This enhances the guest experience and maximizes revenue.

Hotels leverage algorithmic pricing also to implement flash sales and limited time offers. Algorithms consider factors like current room availability and market demand to set optimal promotional prices.

Similar to airline practices, hotels use surge pricing algorithms for last-minute bookings. Prices adjust dynamically as the check-in date approaches, responding to immediate demand.

Moreover, hotels employ algorithms for predictive analytics to forecast future occupancy rates accurately. This allows for proactive price adjustments to align with expected demand. Algorithmic pricing takes into account major events, holidays, or local festivities to adjust rates. This ensures that hotels optimize pricing during periods of heightened demand.

Hotels leverage algorithmic pricing to optimize revenue from ancillary services. This includes dynamic pricing for services like spa treatments, room upgrades, and special amenities.

Again, algorithms analyze guest profiles and preferences to suggest personalized upselling options, enhancing the overall guest experience and increasing revenue from additional services.

To summarize, algorithmic pricing in the hotel industry is a dynamic and multifaceted approach that goes beyond traditional rate-setting models. By incorporating real-time data, personalization strategies, and demand forecasting, hotels can optimize revenue, improve guest satisfaction, and stay competitive in an ever-evolving hospitality landscape.

2.3.3 Technology and Software

In the software and technology sector, algorithmic pricing has become a key tactic that has shaped how businesses set prices for their goods and services. Algorithmic pricing is employed to dynamically adjust subscription fees based on user behavior, feature usage, and market conditions. This ensures that customers pay for the value they receive.

Utilizing user data analysis, algorithms provide individualized membership tiers that adjust features and costs according to each user's unique tastes and usage habits.

Algorithms automatically modify price for software and cloud services with use-based models in response to usage measurements. This makes billing flexible and affordable. For services like cloud computing, algorithms optimize pricing and resource distribution in real-time, guaranteeing economic viability and effective use.

Businesses utilize algorithms also to determine the best prices for product bundles while taking market trends, customer preferences, and past purchases into account. Algorithms analyze user behavior to provide personalized bundle recommendations, enhancing the overall customer experience and maximizing revenue.

Companies can dynamically modify their rates to stay competitive in the market by using algorithms that continuously track competition pricing. Businesses utilize automated price matching algorithms to make sure their pricing remain profitable while matching those of their competitors.

Like in the other sectors, even in the software and technology sector, algorithmic pricing is a dynamic tool that helps businesses maximize profits, improve customer experiences, and maintain their competitiveness in a market that is always changing. Businesses can adjust their pricing models to match client behaviors and market situations by utilizing data-driven algorithms, which will help them succeed over time in this ever-changing industry.

2.3.5 Financial services

In financial markets, algorithmic pricing is fundamental especially for the process of algorithmic trading, where algorithms execute trades at optimal prices in milliseconds. Another use that financial institutions make of this is leverage algorithmic pricing to offer personalized financial products, setting interest rates and fees based on individual risk profiles.

But the most widespread use of artificial intelligence in the financial sector, according to Holli Sargeant, is algorithmic credit scoring. Its prevalence can be attributed to two factors. First, machine learning correlation and classification algorithms are ideally suited to classical statistical credit granting and scoring procedures.

Second, insufficient procedures for evaluating creditworthiness can have a significant influence on capital and earnings as well as repayment capability, credit risk exposure, and erroneous portfolio quality.

Over time, these procedures have been reinforced since banks now assess prospective applications based on past performance and data. Banks' evaluations of customers and credit risk can be greatly enhanced by algorithmic credit scoring, particularly for customers who were previously excluded.

As a result, before making a loan offer, banks evaluate their finances and other pertinent data to decide whether to approve the loan and what the terms of repayment will be (such interest rates). A bank's profitability depends on its ability to accurately choose which customers to lend to in order to minimize risk and optimize the typically thin profit margins of retail banking.

Giving customers access to credit is equally crucial, but only to the extent that they can repay it. For customers, defaulting on a credit agreement, such as a home loan, can have permanent repercussions. As a result, both parties place importance on the choice to join into a consumer credit contract.

As we have understood from this section, algorithmic pricing is revolutionizing traditional pricing models and finding applications in a wide range of sectors. Algorithmic pricing's profound effects on consumer behavior, market dynamics, and competitiveness are becoming more and more evident as companies look for new and creative ways to implement it.

Obviously, all these different applications highlighted in the previous chapter lead to focusing attention on the related ethical, moral and legal aspects, and the whole issue linked to transparency, fairness, privacy and price discrimination deserves a more dedicated section later on.

3. Dynamic Pricing

The first major type of algorithmic pricing—the dynamic kind—will be examined in this chapter. Specifically, a general introduction to the topic, an explanation of how this type is applied, a description of the various strategies, their associated benefits and drawbacks, and a list of the industries in which it is most prevalent will all be covered.

3.1 Definition and key concepts

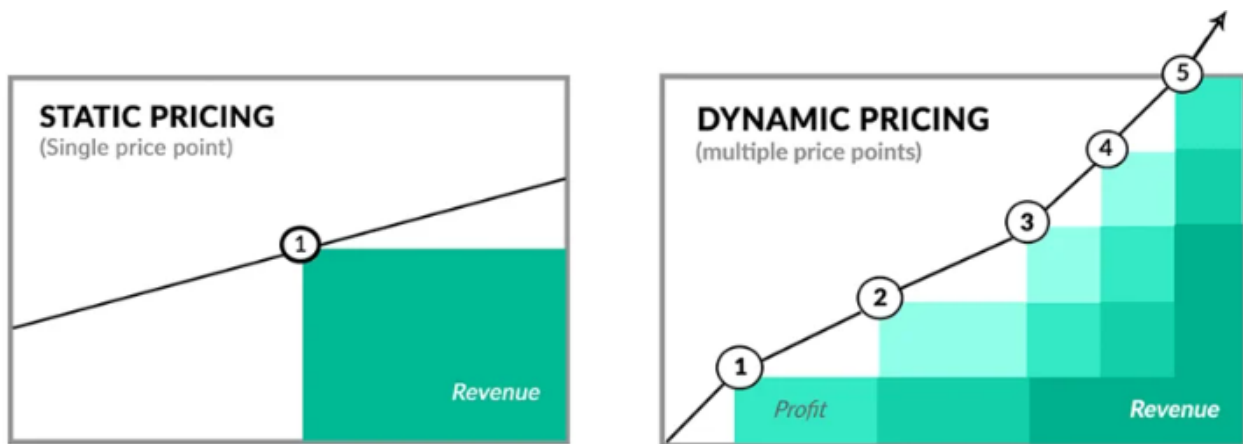
As we've already learned, dynamic pricing is a pricing technique that enables companies to modify the prices of their goods and services in response to many factors like supply, demand, time, and market conditions. This approach varies from the fixed pricing strategy, where prices remain constant for a specific period of time. Many different industries, such as transportation, hotels, e-commerce, and sharing services, employ dynamic pricing extensively.

To fully understand the characteristics of this strategy, it is important to start with the key elements behind it, including:

- **Supply and demand:** dynamic pricing determine the right prices by accounting for fluctuations in supply and demand. For example, during periods of high demand, prices can go up to reflect consumers' higher capacity to pay as well as to manage resource scarcity. On the other hand, in order to increase sales during times of low demand, prices may drop.
- **Customer segmentation:** this allows you to charge different consumer groups differently according to their purchasing habits, inclinations, or potential to pay. This enables companies to optimize earnings and customize products for various clientele groups.
- **Time:** time is a crucial factor and must be considered deeply when prices are set. The time of day, day of the week, and season can all affect prices. For instance, the proximity to the departure or arrival date may affect how much a hotel room or airline ticket costs.
- **Data and analytics:** for the purpose of forecasting supply and demand patterns and figuring out the best prices, dynamic pricing uses data and analytics. Companies can examine historical data and real-time information, such as bookings, cancellations, and competition, using algorithms and prediction models to modify rates.
- **Transparency and flexibility:** in order to promptly adjust to changes in the market and notify clients of pricing changes, businesses must exhibit a certain level of transparency and adaptability. Enterprises need to achieve equilibrium between modifying prices to optimize profits and preserving client confidence and contentment.

Businesses can improve their position in the market and increase profits by using dynamic pricing and they can also quickly adapt their prices to the state of the market; dynamic pricing is based on pre-established pricing rules and it's a tool that allows to promote client loyalty and helps to win over new customers. Moreover, retailers may alter their prices even faster and more effectively thanks to the integration of dynamic pricing with machine learning algorithms, supported by real and reliable data, helping them to differentiate from the competition.

Dynamic pricing can be seen also as the practice of having multiple price points, based on several factors such as customer segments, peak times of service and time-based consumption, through which companies expand its revenue generation. As we can see from the graphs below (Figure 3), there is a notable difference from the standard single price point strategy, in which companies apply the same price level to any customer and market condition; in fact, the area representing the revenues generated by sales is decidedly smaller than the one of dynamic pricing.



Source: Competitoor. Available at: <https://competitoor.com/it/pricing-it/dynamic-pricing/> Figure 2

By now it is clear, at this point in the thesis, that dynamic pricing approaches have been consolidated for some time. However, to better understand the current use of these systems, it is necessary to highlight five fundamental characteristics.

These characteristics are evident in academic research as well as in real-world implementations of dynamic pricing strategies, which are examined in the sections that follow.

We designate these traits as: i) Dynamic Value Orientation, ii) Data Quality, iii) Digitalization of Pricing, iv) Algorithmic-driven decision-making and v) Reduction in Cost of Changing Prices. Each attribute is interlinked, and without the existence of new technologies and datasets these approaches would be impossible to implement. On the other hand, new technologies by themselves would not be sufficient in the absence of managerial desire to innovate in pricing and consumer acceptance of new pricing approaches.

The first, “Dynamic Value Orientation”, reflects the core role of value in pricing, whether value creation or value extraction. The capacity to quickly adjust prices to match value or the capacity to gather and evaluate data to define value limit the ability of traditional pricing approaches to match price to value. Pricing to value can be matched more quickly and accurately with the use of dynamic pricing strategies. In its most basic form, this is demonstrated by "pay what you want" and other participatory pricing schemes that enable quick, real-time, and consequently changeable pricing based on customer choices. Uber's surge pricing strategies provide as an illustration of how to dynamically align price with value production on an individual basis in a way that can create supply.

The second attribute, "Data Quality," highlights the necessity for pricing strategies to be grounded on high-quality underlying data in order to facilitate decision-making. Setting pricing is actually a step in the process, not the last one, in determining value. One of the most difficult market research issues has been figuring out how customers react to different price points. The quality and efficacy of dynamic pricing algorithms are further enhanced by the increasing amount of training data that is accessible for use in pricing choices. In addition to "Data Quality", the "Digitalization of Pricing" is altering how consumers receive pricing information. The amount of pricing given in a digital form has significantly expanded due to the growth of online marketplaces, digital travel purchasing, and online retail. The COVID pandemic's effect on promoting touchless payments and the easy accessibility of mobile devices increased the capacity to provide digital pricing in nearly all environments. This makes it easier to generate context-specific, tailored prices in real time. One example is the adoption of electronic shelf labels in grocery stores, which enable quick adjustments to physical store prices to reflect those on the internet.

The fourth characteristic, "Algorithmic-driven Decision-making," represents a move away from management decision-making toward machine-based decision-making, as the use of algorithms to set prices has become more commonplace.

The autonomy these algorithms exercise and the gap between the human decision-maker and the actual decision-making process both increase with algorithmic sophistication.

Dynamic pricing techniques free pricing agents from reliance on a mechanical rules-based system and allow them to independently coordinate prices without human involvement. Due to the ease of access to these technologies and their low implementation costs, both in terms of the technologies themselves and the degree to which dynamic pricing approaches can be more readily incorporated into business processes, these features contribute to the "Reduction in Cost of Changing Prices." Widespread adoption of these technologies was largely driven by their simplicity of deployment and decreased cost, as the advent of big data has demonstrated.

3.2 Types of Dynamic Pricing

In order to employ a dynamic pricing strategy effectively, it's fundamental to understand how to alter your prices in response to various criteria. Let's discuss the most common forms of dynamic pricing, their characteristics, and the spheres of usage:

The first type is called 'Segment-based pricing': with this kind of pricing approach, businesses can establish prices for various client categories using machine learning or algorithms. Costs differ according to a client's location, social standing, demographics, and other data gathered from public sources. This is the most questionable kind of dynamic pricing since it undermines brand loyalty and image while making higher-paying customer segments feel disadvantaged.

Second, Time-based pricing follows which is often used in online retail, utility pricing, and electricity pricing. It means that prices can change depending on the time of the day or the day of the month. For example, online shops may set higher prices for their products from 9 am to 5 pm, which is a high-demand period.

Then we have Cost-plus pricing, one of the most popular types of dynamic pricing. The price formula is the average fixed cost plus a certain amount of profit. However, several elements, including market shifts, rival pricing, and consumer value, are not taken into account by this technique.

The fourth type is named "Competition-based pricing", maybe the most important one because it keeps track of the competitors' prices, and we know that this is a crucial factor in order to remain competitive in the market; this strategy is often used in e-commerce. For example, Amazon is one of the leaders in the industry and changes its prices regularly, encouraging its competitors to adjust. Businesses tend to collaborate when market competition is strong. Comparable pricing promotes earnings for all businesses and prevents dumping.

Continuing our analysis, we find the Value-based pricing, which deserves a deeper analysis, by the moment that it's seen by economic literature as the strategy replacing the cost-based one. Under value-based pricing, prices are based on consumers' perceived value of a product rather than the cost price of the product with an included markup; we get to this because data-driven marketing strategies have enabled firms to improve the identification of consumers' valuation of goods and services.

In fact, the council of economic advisors of the US stated it as follows:

Big Data has lowered the costs of collecting customer-level information, making it easier for sellers to identify new customer segments and to target those populations with customized marketing and pricing plans. The increased availability of behavioral data has also encouraged a shift from third degree price discrimination based on broad demographic categories towards personalized pricing. (van Heusden, A., 2023)

Finding out how customers value products and services is especially important for marketing research. It is evident that value-based pricing has replaced cost-based pricing in practice, even because the equality between price and value of a product could be satisfied only in an ideal world, and we know that value differs from customer to customer. (van Heusden, A., 2023)

Additionally, it is dependent by the time and retailer. This pricing model has also a variant known as 'conversion rate pricing', which is based on the proportion of website visitors who become customers. Website's prices rise in tandem with an increase in conversion rate. This strategy is used among online shops, and its peculiarity is that customers can influence the products' prices.

The last type is the bundle pricing; according to this dynamic pricing strategy, the price of a product depends on whether it is bundled with other products. The prices for bundled products are lower than the prices of the same products sold separately. Subscription-based platforms, printed media, and online courses often use this dynamic pricing type. (e.g., Netflix, Dazn, Sky)

The methods that were just emphasized are different from how consumers view and react to price adjustments, and particularly from how businesses view and understand this issue. This discrepancy also depends on how feasible strategies for revenue management are in a given market, how much pricing influences consumers' perceptions of value, and—as was previously mentioned—how strategically customers react to price changes. While digitally native businesses like Uber can employ a wide range of pricing strategies, other industries are investigating the use of more dynamic pricing techniques.

As an example, consider the use of subscription and dynamic pricing strategies to increase middle-class and developing nations' access to pharmaceuticals. In services such as hospitality with high fixed costs and low marginal costs, using dynamic pricing for advanced bookings is a key strategic driver of profitability. Customers are able to react to dynamic pricing in these situations since they are accustomed to it. The use of dynamic pricing in highly regulated industries, such energy supply and healthcare, needs to be balanced against the need for more regulatory monitoring and customer protection against unexpected price increases.

Inverse incentives also exist, such as the possibility that prices will promote prosocial consumption like limiting energy use. In retail, the use of electronic store labels provides opportunities for dynamic pricing in physical retail context. Even though efforts have been connected to better customer experiences, consumers' reactions have been characterized by skepticism and poor adoption rates.

3.3 Advantages and disadvantages of dynamic pricing

Having reached this point in the thesis, we have been able to understand what are the advantages, especially from an efficiency point of view, that companies can obtain by exploiting the dynamic pricing strategy; like all things, there are also disadvantages, and some additional ethical challenges, (for the nature of the process), to which due attention must be paid, and which will be analyzed in more detail in next chapters. But now let's see in more detail what these benefits and downsides are.

The first positive effect is that companies can increase revenue without sacrificing sales thanks exactly to the automatic pricing mechanism, giving them the opportunity to spend more on differentiation and innovation. Differentiation and innovation can therefore result in cost savings, better products and services, and ultimately, benefits for the customer. To explain better, using dynamic and customized pricing, the innovative company can increase its incentive to innovate by better recovering its investment. Consequently, an increase in product quality or enhanced personalized services can be expected.

If the market is sufficiently competitive, the innovation will not lead to a monopoly and the pricing practice could benefit consumer welfare. Algorithmic pricing may actually cause the customer poaching effect, which is a stronger competition effect. This essentially indicates that a seller can give a tailored price to a customer that is lower than the competitor's price and attract in business if the seller is aware that the customer is more willing to pay for a competitor's product. The consumer will benefit from increased competition if more businesses use this strategy to draw in customers.

Moreover, certain businesses with high fixed costs may increase as a result of algorithmic pricing. Let's use the example of the airline industry to better illustrate this point. Airlines have comparatively low variable costs and large fixed costs. The airline business was characterized by strict regulation and little competition in the late 1970s and early 1980s. This impeded the industry's expansion, which is why deregulation was promoted. However, the price wars that resulted from the surge in competition pushed airlines to bankruptcy. The primary issue was cross-subsidization and a restricted demand for flights due to uniform pricing. In comparison to their willingness to pay, business travelers spent relatively little, while a portion of the price-sensitive consumer sector was left out because the prices were too high for them.

The industry was able to experiment with segmentation and dynamic pricing with the introduction of internet technologies. This turned out to be a very effective profit-maximizing tactic that was progressively enhanced over time. Taking this example in mind, it's easy now to see how algorithmic pricing could help other struggling businesses with high fixed costs and relatively low variable costs.

Naturally, time savings is another advantage of utilizing dynamic pricing; you stay one step ahead of the competition. Every time there is a more or less major change in the market, you don't have to waste time manually adjusting prices. After you've established your pricing guidelines, the algorithms that track your competitors' prices will adjust on their own to increase their customer appeal and provide you with a healthy profit margin.

In addition, also inventory management can be improved; by adapting prices to shifts in demand, dynamic pricing helps avoid overstocking or stockouts. This reduces carrying costs and possible revenue loss by preventing the accumulation of surplus inventory during slow times and guaranteeing adequate stock during times of high demand. Additionally, dynamic pricing enables companies to maintain inventory levels in equilibrium with seasonal variations in demand. It is possible to prevent surplus inventory at the conclusion of a season by constantly adjusting prices to encourage sales of seasonal products. Furthermore, dynamic pricing reduces the holding expenses related to excess inventories. Businesses can reduce the time inventory stay in storage by modifying prices to increase demand when needed.

It has been also discovered in the economic literature that (algorithmic) price discrimination increases output. Since price discrimination generally enables businesses to service a larger portion of the market, this conclusion is applicable to various marketplaces. Increased output levels allow the business to maximize its manufacturing capacity and boost profits, increasing margin without losing the leading position in the market.

Finally, algorithmic pricing has the potential to help solve other societal issues on a larger scale, which will ultimately benefit both society and consumers. For instance, it has been discovered that by more precisely adapting to variations in demand, tailored pricing can address issues with over- and underconsumption. Additional instances include pricing algorithms' capacity to raise revenue while lowering food waste and enhancing water conservation. Consumers would ultimately gain if the firms' increased productivity brought about by algorithmic pricing is used for socially beneficial objectives. According to Seele et al., the environment and society at large will win by lowering carbon footprints, which is possible with the efficiency increases.

However, there are also negative effects. Firstly, the practice of algorithmic pricing is costly. The expenses of segmentation for a company have decreased dramatically with the introduction of Big Data tools, but they are still there. Costs must be expended whether the company purchases the customer data from a data broker or gathers the data itself. As a result, operating costs, also known as fixed costs, and marginal costs, also known as variable costs, will rise. These expenses must be weighed against the higher profits that algorithmic pricing generates (trade-off). The company must invest in data analytics and artificial intelligence rather than in new product or service upgrades.

Second, algorithmic pricing poses a risk of losing consumer confidence in virtual marketplaces. Consequently, there may be a considerable decrease in demand. When compared to a scenario in which price discrimination does not exist, this would represent a loss of consumer surplus. This is justified by the idea that if consumers lose trust, demand drops, which in turn decreases output levels and reduces welfare. It should be mentioned that if demand were to significantly decline, company earnings would also decline.

Additionally, dynamic pricing could lead to collusion. The algorithmic pricing mechanism gains knowledge on its own by trial and error. It can determine the best pricing strategy by looking at the prices of its rivals. The algorithm is unlikely to select a course of action that creates a price war and wipes out earnings. On the other hand, it usually maintains high pricing in order to produce large profit margins.

AI systems are more inclined to look into collusive pricing strategies that increase profits. Algorithms can also respond immediately to real-time rival action monitoring. Therefore, there is no motivation to defect while breaking the collusive agreement because it can be punished instantly. Thus, the instantaneous monitoring of competitors' prices can aid in the formation and maintenance of higher prices through collusive actions. Empirical and experimental data demonstrate collusive behavior in using algorithmic pricing mechanisms. Moreover, dynamic pricing can increase competition; in the online retail industry, for example, with the availability of price comparison websites, consumers now have an incomparable advantage. An increasing number of internet retailers are competing for the leading position, frequently by cutting prices arbitrarily and without restraint. All of this has the potential to escalate already intense competition and cause price wars in addition to monetary losses.

Finally, another potential problem could be the management of a large database; data capture and analysis are essential for success – especially in the case of large-scale operations. Manually collecting and analyzing such data is nearly impossible in today's e-commerce industry. This is due to both the amount of information and its dynamic changes. For many retailers, managing such a large and unpredictable database can be a real challenge.

4. Personalized Pricing

Once the concept of dynamic pricing has been introduced, and even before analyzing the ethical aspects of the phenomenon (chapter 5), we can discuss at this point of the thesis the second type of algorithmic pricing, the so-called "personalized pricing". Let's see in detail the key concepts, the advantages and disadvantages, and what are the implications for privacy and data security.

4.1 Definition and Key Concepts

Since dynamic pricing, in its traditional sense, entails price changes over time due to fluctuation in supply, demand, competition and other factors, there is no difference between type of consumers; thus, prices are the same across customers at a given time. Personalized pricing, instead, involve sellers dynamically adjusting prices for the same product or service across different 'categories of customers', taking into account factors like browsing and purchase history, IP address, and other identifying characteristics; in this sense, personalized pricing is a special and more evolved form of dynamic pricing.

The evolution of personalized pricing has been fueled by the increasing availability of detailed data on individual purchasing behaviors and preferences. This data is processed through complex algorithms that aim to in-depth understand the profile of each consumer, allowing companies to maximize profits and consumers, who can receive targeted offers; this price customization has been implemented in different industries, from e-commerce to digital services.

Let's start by giving a definition of this phenomena; according to Joost Poort and Frederik Zuiderveen Borgesius, personalized pricing is defined as "differentiating the online price for identical products or services based on information a company has about a potential customer." (Poort, J., & Borgesius, F., 2021)

As we can understand, it's an online form of price discrimination that, in the future, we expected to be more and more prevalent.

Three levels of pricing discrimination are demonstrated by the body of existing literature. Many businesses in the retail industry practice first-degree discrimination, which is centered on the willingness of customers to pay, in order to increase income. Second-degree price discrimination is an effective way to increase revenue where customers can self-identify or self-select to buy at certain prices. For instance, a customer may be able to obtain special benefits and elevate their status for a higher price (e.g., a first-class airline seat for a higher price).

Third-degree price discrimination refers to the purchasing decisions made at different price points within a single product category by distinct customer classes with differing attributes.

In such cases, customers and businesses can both profit from third-degree pricing discrimination; for example, customers who think a product is excellent quality and can afford a higher price, are willing to pay more for it than those who think it is low quality. In this way, firms can obtain more revenue and profit. (i.e., restaurant customers are willing to pay premium prices for special tables with better views or higher levels of service. (Wu, Z. et al, 2022)

In Table 1 we can find a summary table that helps to understand the forms of price discrimination and related phenomena.

	Definition	Examples
Price personalisation	Differentiating the price for identical products or services based on information a company has about a potential customer	
First-degree price personalisation	Differentiating the price for identical products or services at identical time based on personal characteristics of individual consumers	Individual price for a product based on past shopping behaviour
Second-degree price personalisation	Differentiating the price for products or services based on quantity purchased	Family-prices packaging
Third-degree price personalisation	Differentiating the price for identical products or services at identical time for a particular market segment or consumer group	Student discount
Dynamic pricing	Differentiating the price for identical products or services at identical time based on current market demands	Dynamically priced airline tickets
Personalised recommendations/search results	Differentiating the products the consumers sees, commonly based on consumer characteristics	Personalised product recommendation in a web shop

Source: Rott, P., Strycharz, J., and Alleweldt, F. (2022). Personalised Pricing. Publication for the Committee on Internal Market and Consumer Protection Policy Department for Economic, Scientific and Quality of Life Policies. European Parliament. Luxembourg.

Table 1

One of the main factors in figuring out the customized price is willingness to pay. "The maximum price a given consumer accepts to pay for a product or service" is the definition provided by Le Gall-Ely M. (Le Gall-Ely, M., 2009). Retailers attempt to estimate the price a customer will pay for a good or service, and the goal of personalized pricing is to provide rates based on the customer's individual willingness to pay.

Typically, the price determined by willingness to pay is contrasted with a standard or regular price, also known as the reference price. This price can be defined as the price that the same trader would offer to all customers at a given point in time if no price personalization were applied. (Rott, P. et al, 2022)

Two distinct approaches can be recognized for price personalization: automated and non-automated. Our focus will be of course on the automated personalization, where algorithms take the central role and ensure that online store identifies customers through a cookie, an IP-address or a user log-in information and collect data about their willingness to pay for a specific product.

As we mentioned many times in this thesis, this is a process that guarantee multiple benefits for both traders and consumers, and we will explore them deeply in the next paragraph; on the other hand, price personalization may lead to an increase of the reference price, and hamper consumers' ability to compare offers.

Consequently, pricing personalization tends to be seen negatively by consumers. Although they are open to second and third-degree personalization, they believe that pricing that are personally tailored are unjust. Part of the reason for this mindset is the opaqueness of personalization procedures. There are three different ways to be transparent: stating that the price is customized, explaining how customized it is, and describing how it differs from the reference price.

All of these disclosure practices need to be used with caution because behavioral research indicates that the effectiveness of personalized disclosures is influenced by disclosure-related factors like informativeness, comprehensiveness, and completeness, as well as consumer-related factors like motivation, knowledge, and biases.

4.2 Benefits and drawbacks of personalized pricing

There are several cost-benefit trade-offs associated with price customization for both customers and retailers; in this section we analyze them, trying to highlight the critical issues from an ethical point of view.

First, from the perspective of traders, personalization usually involves offering consumers with a higher willingness to pay a higher price than the regular price. This allows traders to maximize their profits. It can also be advantageous for dealers to personalize prices for customers who are willing to pay less than the standard price. The profit per product will drop in this scenario, but a wider range of buyers will find the product appealing due to its lower price. This broadens the target market and raises overall earnings. (Rott, P. et al, 2022) At the same time, this aspect is also advantageous for consumers because allow them to obtain a greater access to the market; certain groups of consumers, mainly those ones with a low willingness to pay, are excluded from the market under uniform pricing.

Through personalized pricing, special discount prices could be offered to these groups, which makes certain products and services to them available that would otherwise not be. Rather than increasing prices to target consumers with a higher willingness to pay, firms could selectively vary prices and offer consumers with a low reservation price a special timely coupon. Making high-value users pay more can counterbalance the cross-subsidization that occurs under uniform pricing, opening the market to low-value consumers.

It has also been discovered that tailored pricing may occasionally result in a rise in consumer surplus. Businesses may choose to pass along the efficiency savings to customers in the form of generally cheaper prices, which enhances the welfare of all consumers. Customized pricing is another effective way to get good feedback from customers. Businesses would then split some of the higher earnings (for example, by offering customer perks) in order to maintain their solid reputation and prevent public outrage.

Finally, some contend that price personalization stimulates greater competition among sellers by enabling them to present a competitive offer to customers. Thus, more competition generally benefits the welfare of consumers. It is not always evident, however, how price personalization affects the average cost of goods and services and, consequently, the welfare of consumers as a whole. Price personalization may result in a net welfare loss even though enhanced competition may benefit consumers if it causes consumers who pay higher prices (based on their presumed higher willingness to pay) to lose more than traders make.

Furthermore, there is also a problem for different customers, from an experience point of view; by this, we mean that price discrimination will most likely be more harmful to naive consumers than to sophisticated consumers. This is justified by the idea that knowledgeable customers will be better able to predict the consequences of price discrimination and adjust their behavior accordingly. As a result, inexperienced customers will ultimately pay higher costs, which will cause them to lose a larger portion of their welfare. If businesses could change their ways to stop this sophistication-based discrimination, this wouldn't happen; but, doing so would need a smart and intentional division of consumers into groups that ranged from the naive to the intelligent. Even yet, unsuspecting consumers will lose out if this categorization turns out to be incorrect. In general, it is anticipated that price discrimination will benefit more knowledgeable consumers than it will unsophisticated ones. Since naive consumers tend to be poorer, less educated, and more vulnerable in real life, the desirability of algorithmic pricing in the context of distributive justice is seriously questioned.

Ultimately, depending on the transparency of the practice, price personalization can result in additional costs for consumers. Low transparency and price personalization may contribute to information asymmetry and inequality. Traders employ a variety of strategies to obtain information about consumers' willingness to pay as well as personal data. However, these customers frequently don't know how their data is gathered or that it might be used for personalization. This also stands valid for the personalized prices themselves; in the absence of adequate disclosures, customers are left with only the prices that are displayed to them, lacking any further details regarding the pricing strategy or comparison to standard rates. As a result, there is an information imbalance where retailers are able to see the price distribution and demand curve far better than consumers. These last ones remain unaware of how the prices displayed compare to the regular prices and are therefore unable to judge whether the personalized prices lead to an advantage or disadvantage. (Rott, P. et al, 2022)

To conclude this section let's try to give an example that can explain better, and to do this let's take the case of the students' discounts proposed by Poort and Zuiderveen Borgesius. Traditionally an example of third-degree personalization, student prices could become more differentiated with the current technology. There might be wealthy and poorer students among the student population. By using personalization approaches, traders can further distinguish themselves from other members of the student community based on factors such as the type of device or neighborhood. Therefore, it is possible to categorize students who may be wealthier as having a larger desire to pay and receive a premium price. Furthermore, since setting an initial higher regular price would allow discounts to be extended to all customers, even those with a higher willingness to pay, it is possible that the appropriation effect would result in a higher regular price. (Poort, J. and Borgesius, F., 2022)

4.3 Taxonomy of Personalized Pricing in Data Protection Law

Let's try to better understand the phenomenon of custom pricing by making a more legal classification of it. This study suggests three different categories of algorithmic pricing: personal data-based algorithms, non-personal data-based algorithms, and affinity-based algorithms. These categories are based on the approach taken in the data protection law addressing the distinction between personal and non-personal data. These three different types of algorithmic pricing are illustrated in Table 2.

Table 2 Taxonomy of online algorithmic pricing		
Type of algorithmic pricing	The processed data	Exemplar uses
Personal data-based algorithmic pricing	Dynamic and Static IP address, various cookies, MAC address, IDFA & IDFV (for Apple products), Device ID (for Android products)	Amazon uses cookies to analyse consumers' browsing history to set prices.
Non-personal data-based algorithmic pricing	Weather, Demand and Require, Delivery Address (to satisfy the purpose limitation principle), time of day, website traffic, historical data, or competitor's prices	Some airlines charge their customers according to seasons or choices of seats.
Affinity-based algorithmic pricing (Group Privacy)	The nature of the data is unclear and may not be covered by data protection law. However, many aspects can be considered influential, such as membership and phone battery information.	Uber charges according to customers' phone batteries; Meituan sets prices based on customers' phone brands

Table 2

Source: Li, Z. (2022). Affinity-based algorithmic pricing: A dilemma for EU data protection law. *Computer Law & Security Review*, 46, 105705.

Personal data-based algorithm pricing, or personalized pricing, is the type which online platforms or sellers generally deploy to create user profiles by collecting users' behavioral data. As previously indicated, Amazon, for instance, creates user profiles using cookie data and applies varying prices to individuals based on their profile and usage patterns. The opacity of internet corporations' algorithms and data processing processes makes it difficult to stop this from happening even after more than 20 years of online business. Similar to this, social media data is analyzed in the insurance sector to create user profiles for risk evaluations, which ultimately influence the cost of the insurance policy.

The data that pricing algorithms utilize to determine rates in non-personal data-based algorithmic pricing has nothing to do with the privacy of the clients. For instance, the weather, demand, season, time of day, and past price data are some examples of variables that affect pricing. The websites of transportation companies are the ones that use this tactic the most frequently. Additionally, some airlines charge passengers based on the seats they select. Similar to this, Uber uses "surge pricing," raising prices during bad weather or periods of high demand. (Li, Z., 2022)

An emerging form of algorithmic pricing that blends dynamic and personalized pricing is called affinity-based pricing. Despite the algorithms' focus on gathering non-personal data, a general understanding of a user's position can be established. Since everyone receives the same offers regardless of their status or property, the price is not thought to be individualized. An person is unlikely to be recognized using affinity data because some groups of people fit into a specific category. This is seen in situations where Uber charges consumers more for low phone batteries and Meituan and Didi charge users based on the brands of their phones. (Li, Z., 2022)

In other words, it is considered that those who own iPhones earn more money and are more prepared to spend more than those who own Android phones, which are often less expensive. Furthermore, platforms may utilize memberships and subscriptions as criterion for charging users because they may believe that these users are more likely to pay and will set a higher price. While it is not possible to identify any particular user using the data used to produce pricing, it does function well with the status of a group of users, which also has a significant impact on consumers. (Li, Z., 2022)

Adopting the suggested taxonomy has two advantages. First of all, it conforms to the structure of data protection law, which facilitates the legal analysis of any situation. Second, the classification aligns with the economic classification of online algorithmic pricing as well as developing technologies. As a result, it is simpler to combine offline price differential with online algorithmic pricing when the economic classification is compatible, which facilitates straightforward analysis.

The above taxonomy makes it clear that algorithmic pricing is more vulnerable to privacy breaches, unfair personal data profiling practices, and seller inferences of affinity data, all of which are dangers associated with the first and third forms of algorithmic pricing. In both cases, merchants have the ability to determine or infer some private information that users do not want to divulge. This violates the user's privacy and has a detrimental effect on their informational liberty. Additionally, by imposing unjust requirements on transactions, vendors may discriminate against specific groups by charging customers based on their profiles or assumed sensitive information. In the non-personal kind, pricing algorithms mostly rely on publicly available data to display prices, which poses less of a risk to consumers' privacy. Price differentiation was actually already practiced offline before to the internet, and in some situations, it is a right that sellers have. This brings us to the next topic: online algorithmic pricing based on affinity and personal data in context of data protection laws.

5. Ethical considerations in Algorithmic pricing

As we have already mentioned in the previous sections, algorithmic pricing, which is now becoming the most widespread practice in the commercial sector, guarantees many benefits to companies, including flexibility, dynamism, efficiency and a dramatic increase in profits, but at the same time questions arise ethics and transparency regarding its use which require serious reflection.

From a specific ethical point of view, there are three main problems that must be analyzed. The first one is of course price discrimination, based on personal characteristics of buyers, such as their geographical location, purchase history, or the device used to access the e-commerce site; this raises concerns about fairness and social justice.

The second one is the concern about corporate goals versus public interest; pricing algorithms are often designed to maximize corporate profits, and this results in an open debate regarding whether these systems should also consider the public interest, for example, by maintaining affordable prices for certain essential goods. Serious questions emerge in this analysis:

- Are they used in a legitimate way?
- Where is the line between use and abuse?
- How far is it an instrument used for legitimate or speculative interest?

The last focus is on the transparency of decisions; the opacity of pricing algorithms is a significant ethical issue. Buyers have the right to know the factors influencing price determination and understand how their personal data is taken into account; here it's necessary to understand if they are they used transparently and fairly, or in a covered way.

If we go ahead of this last discussion and we specifically consider the point of view of transparency, the first main issue is precisely the accessibility of information; companies should commit to providing detailed information about the algorithms used for price determination. This may include disclosure of variables considered, data sources, and calculation methodologies. Then, the concern of the impact of algorithmic decisions follows; buyers must be aware of the impact that algorithmic decisions can have on pricing formation and their purchasing experiences. Precisely on this topic and in particular for dynamic pricing form, according to Seele et al.

consumers have started to become more strategic in their online shopping behavior. For instance, they often plan their purchases or check prices and inventory management ex-ante, to form a strategic response, even if it remains a challenging task to recognize price changes and to make correct predictions about future price developments. In this way, transparency should also extend to any corrections or adjustments made by algorithms over time. (Seele, P. et al, 2021)

The last focus must be necessarily on privacy protection; in the context of algorithmic pricing, privacy protection becomes crucial. Companies must ensure that users' personal data is treated in accordance with privacy regulations and implement adequate measures to prevent potential abuses.

Let's focus now on a more detailed and in-depth analysis about price discrimination and fairness of dynamic pricing, trying to explain what types of discrimination occur and how customers approach to them, and in a second part, we will shift the focus more on transparency and explainability.

5.1 Price discrimination and Fairness

Algorithmic price discrimination occurs when online retailers use big data and algorithms to charge repeat (loyal) customers higher prices than those charged to new consumers for the same goods and services during the same time. This kind of pricing discrimination involves businesses offering a product at different costs to distinct customer classes with varying attributes. In addition, algorithmic price discrimination sets multiple prices for the same product depending on the desire of the customer to pay in order to maximize profit. As a result, the product's price changes depending on how much customers are willing to spend. The stronger the willingness to pay (loyalty) the consumer has, the higher the price they will be charged. In this sense, algorithmic price discrimination is different from the discount or promotion. (Wu, Z. et al, 2022)

When a new customer buys the same goods at the same time as a regular customer and the latter pays more, the loyal customer feels betrayed that the supplier is being unfair.

Betrayal occurs when buyers or customers feel that sellers have betrayed them, deceived them, tried to take advantage of them, betrayed their trust, broken promises, or revealed private information. These situations can have disastrous effects on the party that is most vulnerable as well as the success of the business relationship.

As we have already seen in chapter 4 there are three existing degree of price discrimination, that bring several issues, especially when it comes to unfair pricing. For example, a variety of online platforms contain ever-more-detailed information about their users, such as demographic (age, location, gender) and behavioral (browser history, device type, purchase prices, and times) data, which, in the case of monopolies, may lead to price discrimination.

Customers may view algorithmic price discrimination as unfair as a result, especially if they become aware of price discrepancies and this presents a challenge. According to studies, customers frequently see dynamic pricing as unfair, particularly when they perceive pricing schemes to be inherently discriminatory.

Finding a balance between the advantages of customized pricing and the fairness that customers feel is the difficult part. Maintaining ethical standards in algorithmic pricing requires making sure that pricing strategies are accountable, transparent, and do not result in unfair discrimination.

Some specific tactics, such giving external reference prices, providing extra incentives like discounts or coupons, and structuring prices in ways that make them appear more desirable, can be used to counteract the possible unfavorable perceptions of algorithmic pricing.

5.2 Transparency and Explainability

The transparency and explainability of algorithmic pricing are crucial aspects to ensure accountability, trust, and ethical use of these systems.

Transparency refers to the clarity and openness with which algorithmic pricing systems operate. It is essential for consumers, regulators, and stakeholders to understand how prices are determined to build trust and ensure fairness. The complexity of algorithms and the vast amounts of data involved in pricing decisions often make it challenging to achieve transparency. Lack of transparency can lead to a lack of trust and potential ethical concerns.

Explainability is the ability of an algorithmic system to provide clear, understandable reasons for its decisions. In algorithmic pricing, explainability is critical for consumers to trust and accept pricing outcomes. In regulated industries, explainability is essential for compliance with legal requirements. It allows businesses to demonstrate adherence to regulations and provides authorities with insights into pricing decisions.

The real issue is that many machine learning models, including those used in algorithmic pricing, are often perceived as "black boxes" because their decision-making processes are not easily understandable.

Efforts to open these black boxes could be a possible solution in order to mitigate this risk; companies should in fact provide stakeholders with clear insights into the decision-making process by documenting them of their algorithmic pricing models and highlighting the major elements that impact pricing decisions.

Also developing user-friendly interfaces that present pricing information in an easily understandable format can enhance transparency. Visualizations and interactive tools can help users comprehend complex pricing algorithms.

Designing systems that prioritize user understanding, like those just mentioned above, could help to develop transparent and explainable algorithms and contribute to informed consumer choices and reduce the risk of perceived unfairness.

In conclusion, explainability and transparency are critical components of algorithmic pricing's moral application. By making sure pricing algorithms are transparent and accountable, regulators and consumers can become more trusting of one another, which help to mitigate potential ethical concerns.

5.3 Collusion issues

Let's move forward to another source of concern, namely the possibility that algorithmic pricing may facilitate collusion: this concern has been repeatedly voiced in recent years, both in the popular press and in the academic literature, evidencing the risk that algorithmic pricing may inhibit competition and effectively sustain collusion with no need of human intervention. The issue is now on the radars of various antitrust agencies, such as the US Federal Trade Commission and the European Commission. (Calvano, E. et al, 2019)

But let's start from the beginning trying to understand what collusion is; we start from the assumption that firms seek to maximize their profits. Prices equal marginal costs in a perfectly competitive environment, all businesses make no profit, and the economy achieves its optimal result. Competing companies could boost their earnings if they united as one dominant company, or if they formed a cartel. Competing businesses in the same sector will enter into a horizontal agreement in order to attain this outcome. Similar to a monopoly, a cartel gives companies the ability to set the price and quantity that they will fix in the market due to their market dominance. Because of the increased pricing, this results in a decline in consumer welfare.

Even worse than monopolies, collusion results in inefficiencies because coordinated but independent enterprises are not able to take advantage of economies of scale, unlike monopolists. Moreover, innovation is inhibited for collusive enterprises because it goes against the agreement to develop new products or enhance old ones. Because of this, high prices and limited market innovation reduce society's overall welfare, which is why most jurisdictions view openly committing to create a cartel as illegal.

Businesses might enter into this kind of agreement in a few different ways. The most prevalent one is price fixing, which occurs when businesses decide to set the same supracompetitive pricing; nevertheless, we shall go into more detail about this subject in a separate section. Businesses could agree to limit the supply of an item or service in order to achieve a similar result by reducing supply; having a lower supply allows firms to increase prices and thus increase profits.

The third way is through market sharing, an agreement between rivals on how to divide the market or clients among themselves. Finally, bid rigging enables companies to band together by determining who will win an auction. As previously stated, collusion is considered unlawful. It is crucial to differentiate between two types of collusion: explicit collusion, which occurs when businesses communicate openly about their agreement, and implicit collusion, or tacit collusion, which occurs when businesses work together to form a cartel without making it clear. And it is precisely in this area that the research we wish to concentrate on falls, as the usage of algorithmic prices amongst businesses unintentionally results in a type of implicit collusion; businesses act in tandem to minimize competition and maximize joint profits.

Price-following algorithms are the first example of tacit collusion because they are made to track and match competitors' pricing, which might unintentionally result in a situation where businesses follow competitors' prices. A feedback loop comparable to tacit collusion may arise when rival algorithms automatically alter their own pricing in response to a price adjustment made by one company. Additionally, algorithmic pricing's openness can improve market monitoring tools. Due to the ease with which rivals can study one another's pricing tactics, companies may unconsciously coordinate their pricing decisions to avoid strong competition.

Another type of cooperation is known as "Hub and Spoke," in which several organizations coordinate their price plans via a single hub. In the context of algorithms, this can entail businesses exchanging pricing information or tactics via a third-party platform, which could result in coordinated pricing decisions that disturb market dynamics.

Last but not least, because algorithms are capable of learning and are sensitive to market conditions, they can eventually settle on comparable pricing techniques even in the absence of explicit communication. Prices could end up higher as a result of this parallelism than they would in a more competitive market.

Research on how algorithmic pricing affects tacit collusion is still in its infancy, but continued attention is needed to guarantee that consumer interests are safeguarded, and market competition is fair. In order to address potential anticompetitive problems originating from algorithmic pricing techniques, regulatory bodies are looking into these issues more and more.

5.3.1 Supracompetitive prices in competitive markets

Even in the absence of coordination, corporations are able to charge consumers supracompetitive prices due to competition among pricing algorithms. Standard elements of algorithms that are currently widely used, especially at the biggest online shops like Amazon and Walmart, are what cause these effects. As opposed to algorithmic collusion, which depends on some level of firm-to-firm cooperation in order to drive up prices, the harms that we identify can be caused by a single corporation using an improved algorithm. This threat to consumer welfare is, in some ways, more significant than that posed by explicit or tacit collusion, which require more stringent market conditions to be successful, because it is likely to influence most marketplaces where prices are established algorithmically. In competitive marketplaces, pricing algorithms enable supracompetitive pricing in two ways.

They first enable certain businesses to adjust prices more quickly than others. A company with an advanced pricing algorithm, for instance, might be able to reprice its goods frequently, even several times a day, whereas a company with a less advanced algorithm would only be able to do so once a week. Faster algorithms allow a company to undercut competitors' prices without fear of a corresponding response, giving it a competitive advantage. The slower firm's incentives to compete on price may be limited if it believes that the faster firm's capacity to swiftly cut prices poses a danger. Knowing that it will lose some customers to its faster competitor, the slower company will set its pricing higher than the market rate.

The quicker competitor then selects a price that is higher than the level of competition but yet lower than its rival's pricing, gaining market share and supracompetitive margins. Due to this uneven frequency, both businesses will raise their prices over what is considered competitive, and customers will end up paying more for their goods overall. (MacKay, A., & Weinstein, S. N., 2022)

A second way in which pricing algorithms lead to higher prices is through a commitment to pre-specified pricing strategies. In order to update prices, algorithms usually encapsulate a set of instructions in software. This software is then used to update prices multiple times before the instructions are altered.

The algorithm enables a company to commit to a pricing plan ahead of time in this way. An algorithm that can autonomously monitor and respond to competitors' price changes gives a firm an advantage over one that lacks this technology, just as a quicker algorithm gives a firm a threat to undercut slower rivals. (MacKay, A., & Weinstein, S. N., 2022)

When firms with superior technology commit to this strategy, firms with inferior technology know that their rivals can be relied on to undercut their prices.

Like with asymmetric frequency, all firms will charge more in this circumstance of asymmetric commitment. In addition to harming consumers, increasing prices in both cases may also result in decreased output and overall welfare.

It's critical to stress that, despite charging supracompetitive pricing, the businesses in these instances are not acting in cooperation. Either explicit or tacit collusion necessitates short-term losses for long-term profits for every firm. The foundation of antitrust action against collusion is the discovery of a firm consensus to promote these kinds of short-term concessions. Instead, we concentrate on situations when every firm acts independently to further their own reasonable self-interest; in these cases, agreement is not required. Furthermore, collusive regimes and algorithmic competition are distinguished by certain notable features. Businesses should set comparable pricing in a collusive market and implement a reward-punishment scheme to rein in price-cutters. Under these kinds of regimes, a single price decrease is penalized by a protracted period of even more significant price cuts by competitors, which lowers the profits of all businesses. In the markets we describe, reward-punishment schemes and identical prices are neither required nor expected. Interestingly, even though businesses may charge wildly disparate prices, they are all greater than what buyers would pay in a market where there is competition.

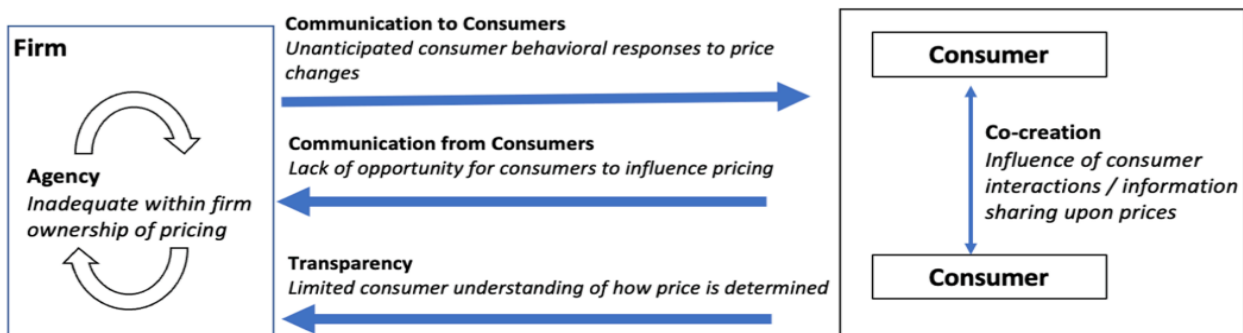
The key distinction between the model we provide here, and algorithmic cooperation may be that a single company might start a vicious circle of harm to consumers only by using a better pricing algorithm. Amazon is one of the companies that already uses algorithms for pricing that are better than those of its competitors.

The issue this section deals-non-collusive algorithmic pricing leading to higher consumer prices-is likely both more ordinary than explicit or tacit collusion and more difficult to remedy. (MacKay, A., & Weinstein, S. N., 2022)

This behavior is outside the present jurisdiction of antitrust law, even in its most expansive interpretation, as we are by definition dealing with competitive marketplaces in which businesses are not conspiring. How can governments deal with emerging risks from technology that exceed established legal restrictions? Direct price regulation is one potential solution.

5.4 Source of perceived pricing inequity

In Fig. 4 it's shown a model that highlights the sources of perceived inequity that are generated through use of dynamic pricing approaches. An understanding of inequities created by the use of dynamic pricing needs to be supported by a corresponding understanding of consumer concerns. This model recognizes that price inequity is not only driven by a dyadic relationship between firm and customer, but also by more complex relationships between stakeholders. The importance of stakeholder-based models of management decision-making that take account of the consumer perspective is becoming more recognized and widespread. Marketing occurs within a broader framework of institutions, and relationships between different groups of stakeholders play an important role in determining marketing outcomes. In this case stakeholder relationships include both within firm and between customer relationships. Four drivers of perceived inequity are identified: agency, communication (both to and from consumers), transparency and co-creation. The concepts of agency and transparency are related to overall control of decision-making within organizations. Perceived inequity driven by communication failures relates to the consumer's lack of ability to influence pricing decisions and by the firm's inability to anticipate the behavioral consequences of the algorithm's changing prices. If consumers don't understand what is driving price changes and cannot communicate their findings, the chances for perceptions of inequity increase. Finally, there are interactions between consumers. (Nunan, D., & Di Domenico, M., 2022)



Source: Nunan, D., & Di Domenico, M. (2022). Value creation in an algorithmic world: Towards an ethics of dynamic pricing. *Journal of Business Research*, 150, 451-460.

Figure 4

This could include both market-based competition among consumers and forms of consumer co-creation where consumers are able to share information about pricing via social media to “beat” the algorithm. Whilst cocreation is typically framed as a route to value creation, this can also create information asymmetries that reduce value for certain consumers. For example, individuals have different “social graphs” and different levels of engagement with online information. Groups with lower access to information, including vulnerable groups, might inadvertently end up paying higher prices.

6. Ethical debate and potential solutions

This section's objective was to present a managerial framework for handling the moral dilemmas brought up by the use of dynamic pricing techniques. A symptom of these moral dilemmas is stakeholder opposition to dynamic pricing strategies. Owing to the intricacy of dynamic pricing, opinions about reference prices are more influenced by opinions about fairness than by past purchasing experiences. Managers must implement tactics that take these perceptions of fairness into account when dealing with the difficulties posed by dynamic pricing. Using the stakeholder model from Figure 5, Table 3 offers strategies managers might use to overcome this opposition.

There are five identified forms of resistance: i) Customers believe they have little control over pricing; ii) Limited agency within firms; iii) Firms do not communicate prices to customers; iv) Ignore consumer to consumer communication; and v) Social perception. We include traits, concrete instances, and strategies managers can use to deal with these issues for each Failure to take account of stakeholder perceptions is likely to result in a range of negative outcomes, ranging from negative customer experience through to pressure from competitors or policy makers. (Nunan, D., & Di Domenico, M., 2022)

The tools accessible to managers to resolve concerns over the usage of dynamic pricing are shown in Table 3. Customers are more likely to consent, for instance, to the use of their data for dynamic pricing if they have an opt-in mechanism in place, like a cookie-style notification. Managers must embrace a trade-off in order to provide customers some control over the data that is gathered and how it may result in some customers choosing to opt out. Customers will also be more likely to trust dynamic pricing strategies as a result of this. Managers who reject this trade-off ought to take into account the cautionary story of consumers losing trust in businesses when consent is not requested, as well as the increasing regulatory scrutiny surrounding social media data collecting. These resistance strategies vary throughout businesses and sectors. (Nunan, D., & Di Domenico, M., 2022) Although dynamic pricing plays a significant role in almost every industry, the individual characteristics of each sector determine how dynamic pricing is implemented and how quickly it is adopted. A more detailed strategy is needed to account for the various difficulties managers encounter based on the industry in which they work. This table's significance lies in highlighting the variety of stakeholders that have the ability to affect dynamic pricing. In order to overcome resistance to dynamic pricing, it is necessary to acknowledge that customers are (tacitly) influencing prices more and more. As a result, it makes sense that they should be more aware of the processes involved in setting prices. Managers need to understand that attempting to force technologies on customers results in a major power imbalance and ultimately destroys trust, which is why they should prioritize.

Addressing Stakeholder Resistance to Dynamic Pricing.

Source	Characteristics	Example	Mitigations
Consumers perceive lack of control over pricing.	Consumers ability to control price impacts perceptions of fairness (Vaidyanathan and Aggarwal, 2003)	Consumers adopt information searching behaviour designed to minimise accurate information collection, such as clearing cookies or use of a VPN or adblockers.	<ul style="list-style-type: none"> • Informed consent: Provide consumers with details on which data points influence price, and options to opt-out. • Illusion of control: Provide variables that consumers can manipulate (e.g. time-based pricing) or suggest approaches that consumers can use to change pricing.
Limited agency within firms	Failure of employees to understand impact of dynamic pricing / algorithmic decision making on consumers. Lack of multi-stakeholder perspective.	Unwillingness to implement dynamic pricing due to fears of consumer backlash (Priester et al. 2020).	<ul style="list-style-type: none"> • Approaches to use of dynamic pricing should take a customer lifetime value approach. • Carry out market research & customer insight work on consumer perceptions to dynamic pricing before implementing pricing changes.
Absence of firm to Consumer Price Communication	Consumers use heuristics to determine motivations behind algorithmic pricing and techniques being.	Many consumers believe use of dynamic pricing-based on person data is illegal (Turow & Hennessy, 2015)	<ul style="list-style-type: none"> • Develop policies to communicate where dynamic pricing approaches are used to consumers and explain approaches in terms of value creation. For example, that dynamic pricing maximises capital investments and keeps prices down overall.
Ignoring Consumer to Consumer Communication	Consumers determine reference price-based on lateral consumer relationships.	Consumer perceptions of price information-based on information on comparative information available on social media (Lee et al. 2011)	<ul style="list-style-type: none"> • Counter misinformation about dynamic pricing. Where consumers share pricing information be proactive in providing transparency via accurate information. For example, airlines that share the range of prices that consumers have paid for a flight on particular days.
Societal perception	Dynamic pricing used to exploit customers and maximise profitability.	Greater regulatory focus on dynamic pricing (Borgesius and Poort, 2017)	<ul style="list-style-type: none"> • Engage with policy makers in a transparent way, and frame dynamic pricing as maximising investment. • Ensure that unfair aspects of dynamic pricing are identified and mitigated through manual adjustments.

Source: Nunan, D., & Di Domenico, M. (2022). Value creation in an algorithmic world: Towards an ethics of dynamic pricing. *Journal of Business Research*, 150, 451-460.

Table 3

Continuing and shifting our analysis towards an economic point of view, considering collusion issues and supracompetitive prices mentioned above, according to a study conducted by Yeshiva University (School of Law, New York), there are several solutions (and potential) to overcome these issues. Direct regulation seems to be the best one, for ameliorating the transfer of surplus from consumers to sellers that algorithmic pricing makes possible. This because antitrust law can reach only a select few types of pricing conduct, none of which are implicated by the non-collusive algorithmic pricing strategies described in the previous section. (MacKay, A., & Weinstein, S. N., 2022)

This is not the first time that advances in pricing technology have led to economic disruption. In the early twentieth century, the introduction of price displays, price tags, and new pricing strategies like loss leaders contributed to fierce price-cutting and a dangerous deflation that exacerbated the economic shock of the Great Depression. The policy response then was direct pricing regulation: legislation and industrial codes limiting price cutting.

Price control was another type of direct intervention; in spite of the country's strong policy preference for free market principles, price controls have a long history in the US, particularly during times of emergency. For instance, price restrictions were put in place during the Korean War and both World Wars, when there was intense public anxiety over uncontrollably high inflation.

The minimum wage, which sets a floor on the cost of labor, rent control, which sets a limit on the cost of housing, and anti-usury laws, which establish a ceiling on the interest charged on loans, are other well-known examples of price controls. The federal government capped the price of gasoline twice in the 1970s. Price controls are still regarded as a useful instrument for regulation. In fact, recent proposals to address the exorbitant costs of some medications have called for price limits. In 2021, the U.S. House of Representatives reintroduced a bill that would require the U.S. Department of Health and Human Services to negotiate maximum prices for certain drugs, including insulin and drugs that do not face generic competition. (MacKay, A., & Weinstein, S. N., 2022)

The majority of economists' negative opinions about price controls are perhaps not surprising. According to the conventional wisdom, direct government interference in markets usually has no effect and leads to harmful economic distortions like surpluses or shortages of goods whose prices are supported by price floors or caps on the prices of goods. Price limitations frequently result in illegal markets and rationing as well. Economists believe price controls are suitable only in temporary circumstances, if they support them at all. Compared to price gouging during a war, for example, the increased prices that algorithms can create are probably neither an emergency nor temporary, as it appears that algorithmic pricing is here to stay. Moreover, price restrictions are a crude tool that would be difficult to apply to the millions of items and thousands of markets that algorithmic pricing may touch. A price control system would result in a long-term, significant expansion of the federal government's engagement in the market and need the creation of a new bureaucracy to set prices. These implications recommend against price regulations in favor of a more focused approach that targets the markets where algorithmic pricing is driving up prices and decreasing consumer welfare. To put it briefly, regulating the algorithms itself is probably the most effective way to address the issues that algorithmic pricing presents.

Pricing algorithms provide a number of threats to consumers and competition, some of which can be addressed by antitrust law and some of which may need for regulatory action. Pricing algorithms are a tool that businesses can employ to support overt cooperation, such as price-fixing. Section 1 of the Sherman Act imposes criminal penalties on these kinds of schemes. Pricing algorithms may also make it possible for businesses to participate in tacit collusion, which is now illegal under antitrust law, more successfully. As was previously mentioned, researchers have suggested recommending governmental actions as well as extending the antitrust laws to cover tacit collaboration.

Pricing algorithms can hurt customers by enabling rival businesses to charge prices that are supracompetitive even in the absence of coordination. (MacKay, A., & Weinstein, S. N., 2022)

As explained above, the two key characteristics that empower pricing algorithms to facilitate higher prices are asymmetries in pricing frequency and the ability to commit to an automated price response to changes in rivals' prices. Accordingly, an effective regulatory approach might be based on eliminating one or both of these characteristics. This would mean either barring asymmetries in pricing frequency or prohibiting firms from incorporating rivals' pricing in their algorithms.

We will not explore deeper these last two solutions, but rather we limit ourselves to mentioning them and recognize that regulation is not the only possible response to higher prices brought about by pricing algorithms; market-based strategies are also available. Customers may react to algorithmic extraction by altering their behavior if there is no restriction. Customers might utilize price comparison websites more often or employ algorithmic methods to find reduced pricing. Insofar as they lower search costs and encourage customers to select websites with the best deals, these tactics might offer a way to counteract some of the pricing consequences of algorithms. Although users cannot directly reverse the impacts of algorithms, they can spend money on tools that increase their price sensitivity. But even if these technologies proliferate, the possible consequences of algorithms that persist would make regulation an enticing course of action. (MacKay, A., & Weinstein, S. N., 2022)

We still don't fully understand whether and how pricing algorithms might coordinate on high prices, or whether it's easier for computers to collude than with humans.

To determine if algorithmic pricing actually presents new challenges for competition policy and how these challenges should be addressed, more interdisciplinary study is required. However, the analysis that has been done thus far might provide some insight into the current discussion and the suggested course of action.

In general, three different strategies can be distinguished. The first is to maintain the status quo, predicated on the sanguine belief that algorithmic pricing does not in fact provide any novel challenges.

The second strategy is to control the release of pricing algorithms ex ante, much to how new medications are marketed: a regulatory body should evaluate any new pricing algorithm to determine if it shows signs of collusion (which would make it illegal) or not (which would make it acceptable). Finally, the third approach, involves regulating ex post using different legal criteria than those now in use, much like competition policy generally does. This strategy, in particular, urges a reevaluation of the controversial question of the ban on tacit collaboration. An absolute ban on algorithmic pricing is a potential fourth alternative.

However, there is a wide consensus that pricing algorithms may deliver big efficiency gains by allowing more efficient pricing. A per se prohibition of algorithmic pricing is therefore unlikely to be optimal—even if we set aside the enormous problem of implementing such prohibition in practice.

Let's try now to discuss about the possible concrete solutions to overcome the ethical issues in adopting algorithmic pricing strategies, taking into consideration the points of view of the government, the end customer, and the company. (Calvano, E., et al, 2019)

The first main player is certainly the government, which regulation can play a crucial role; here are possible ways:

- **Mandatory transparency requirements:** Governments have the authority to impose laws requiring businesses to disclose their pricing algorithms. This could entail revealing the data that is used, the methodology used to calculate prices, and any potential biases. Transparency helps authorities better track possible ethical problems and empowers consumers to make better informed judgments.
- **Anti-discrimination laws:** Laws against discrimination that specifically address algorithmic discrimination in pricing can be passed by governments or enforced already. These regulations might make it illegal for pricing algorithms to base prices on some protected traits (such age, gender, or race). Businesses that use discriminatory pricing tactics can be observed by law enforcement agencies, and consequently they can be penalized.
- **Ethical guidelines for algorithmic pricing:** Governments can create specialized ethical criteria for pricing algorithms in collaboration with business stakeholders. To make sure that pricing algorithms adhere to moral norms, these recommendations can specify best practices for algorithmic design, data usage, and transparency.
- **Regulatory sandboxes:** Regulatory sandboxes, where businesses can test pricing algorithms under regulatory supervision, can be established by governments. This enables regulators to create suitable legislation without impeding innovation and to obtain insight into any ethical dilemmas.
- **Oversight and accountability mechanisms:** Governments can set up regulatory or oversight organizations whose job it is to keep an eye on pricing algorithms and enforce moral guidelines. These organizations have the authority to punish businesses that break rules by conducting audits, investigations, and penalties.

By implementing these regulatory solutions, governments can help mitigate the ethical risks associated with pricing algorithms and ensure that they are used in a fair and responsible manner.

The second actor involved is the end customer, who, through specific education programs, can be more aware of algorithmic pricing practices and make more informed decisions. Here are possible solutions:

- **Understanding algorithmic pricing:** Inform customers on the operation of custom pricing algorithms, machine learning, and data analytics in algorithmic pricing. This could entail outlining how costs might change depending on the location, browsing history, and time of purchase, among other things.
- **Spot price discrimination:** Customers should be trained to spot indications of price discrimination while making purchases online, such as price differences based on browsing patterns or demographic data. To prevent tailored pricing, customers can learn how to use incognito mode, remove cookies, and compare costs across several platforms.
- **Data Privacy and Consent:** Increasing knowledge about concerns related to data privacy and the significance of informed permission in the gathering and use of data. Customers must be aware of their rights under data privacy rules and how companies utilize their personal information to customize prices.
- **Ethical Consumption Choices:** Encourage customers to support companies that uphold ethical standards and fair pricing policies in order to promote ethical purchasing choices. Customers have the ability to provide preference to businesses that promote equality and justice over those that are opaque about their pricing policies.
- **Consumer advocacy and reporting:** Give customers the tools and direction they need to report instances of discriminatory algorithmic pricing or unfair pricing practices. Information about how to submit complaints with government authorities, consumer advocacy groups, or the business itself may be included in this.
- **Critical Thinking Skills:** Give customers the critical thinking abilities they need to assess pricing information critically and challenge the legitimacy and fairness of pricing policies. It is important to encourage consumers to investigate and evaluate pricing trends, evaluate costs, and, if needed, seek out alternatives.

By incorporating these elements into consumer education programs, individuals can become more empowered to navigate algorithmic pricing strategies ethically and responsibly.

From a company perspective, addressing ethical issues related to algorithmic pricing strategies requires a proactive approach to ensure fairness, transparency, and accountability. Here are some possible ways:

- **Ethical Design and Testing:** Businesses ought to give ethical considerations first priority when developing and deploying algorithmic pricing systems. Before deployment, this entails carrying out extensive testing to detect and reduce any potential biases or discriminatory effects.
- **Transparency and Explanation:** Businesses have to endeavor to render their pricing algorithms plain to customers by furnishing lucid explications of the methodologies employed to ascertain rates. This enables customers to comprehend and assess pricing selections while also fostering a sense of accountability and trust.
- **Fairness and Non-Discrimination:** Businesses ought to put in place safeguards to make sure that their algorithmic pricing tactics don't unjustly target particular customer groups with discriminatory intent. This could entail establishing standards for appropriate pricing procedures and routinely checking algorithms for bias.
- **Human Oversight and Intervention:** Although algorithms are a major factor in pricing decisions, businesses should also have human oversight to check and correct any instances where algorithmic results raise moral questions. Human judgment can reduce the possibility of unforeseen consequences and give context.
- **Stakeholder Engagement and Feedback:** Businesses should actively seek advice and feedback on their pricing strategies from all relevant parties, such as regulators, advocacy groups, and consumers. This can encourage cooperation in the search for answers and assist in spotting possible ethical problems early on.

By implementing these solutions, companies can navigate the ethical challenges associated with algorithmic pricing strategies while promoting fairness, transparency, and trust in their business practices.

All these aspects just discussed could be useful for consumers, marketers, to reduce the negative perception and mitigate the risk of the pricing algorithms. Let's see how far these tools will go and how the situation will evolve in the next future. It will be a great challenge for everyone.

7. Conclusion

The analysis conducted in this thesis highlighted the growing importance of algorithmic pricing in the contemporary business landscape and underlined its ethical and social implications, which are often a source of debate and concern. The increasing adoption of pricing algorithms has highlighted some crucial issues that require immediate attention from institutions, businesses, and society.

One of the main concerns raised is the possible discrimination resulting from algorithmic pricing. The use of algorithms can lead to discriminatory practices against certain social, ethnic, or economic groups, amplifying existing inequalities and violating the principles of equity and social justice. It is therefore crucial to develop policies and regulations that regulate the use of algorithms in pricing processes, ensuring that they do not result in unjustified discrimination.

In addition, the opacity of the algorithms used in pricing represents an additional obstacle to transparency and accountability. Often the logic behind these algorithms is obscure and difficult to understand even for insiders, making it difficult to assess their correctness and impartiality. It is necessary to promote the transparency of algorithms, through the adoption of standards that require companies to make public the decision-making logic of their algorithms and to allow adequate supervision by the competent authorities.

Another major challenge is consumer protection. Pricing algorithms can be designed to take advantage of consumers' lack of information or vulnerability, causing them to make impulsive purchases or pay unfair prices. It is therefore crucial to promote consumers' digital literacy by providing them with the necessary tools to understand and assess online pricing dynamics, as well as to protect their rights as consumers.

To ensure a non-discriminatory and equitable use of algorithmic pricing and to maximize collective well-being, it is necessary to adopt a multidimensional approach involving different stakeholders. Government institutions must take the lead in the development of public policies that regulate the use of algorithms in pricing processes, ensuring the protection of consumer rights and the promotion of fair competition. Businesses, on the other hand, must commit to implementing ethically responsible pricing practices and ensuring the transparency and accountability of their algorithmic decisions.

Finally, it is important to encourage the research and development of pricing algorithms that are oriented towards the common good, that consider not only the economic interests of businesses, but also the needs and rights of consumers and society. This requires a joint commitment by the academic community, industry, and public institutions to develop innovative and sustainable solutions that promote fair and responsible use of technology in the digital economy.

In conclusion, algorithmic pricing represents a complex challenge that requires a holistic and collaborative approach to be successfully addressed. Only through a joint commitment of institutions, businesses and civil society can we ensure that the use of algorithms in pricing processes is ethically acceptable, socially responsible, and oriented towards collective well-being.

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