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AI-driven profits by AI pricing methods.

Collusion evidence in the digital business world.

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Abstract

Artificial intelligence's emergence has altered the industry and created new dynamics in terms of opportunities, efficiency, and accuracy. Digital markets have already harnessed the possibilities that AI brings in all sectors and have incorporated it into dynamic pricing procedures, they were already implementing digitally for a long time. AI, as part of Machine Learning, develops according to the most recent technological innovations. Thus, firms using reinforcement learning pricing algorithms in the digital marketplace, become more efficient in rapid price adjustments. Recent scientific studies, both in the fields of economics and law, stressed the concern of competition distortions, and more precisely the problem of algorithmic tacit collusion due to pricing algorithms' autonomous behavior. The scope of this Master's thesis is to clarify the consisting elements of the problem under discussion in a single work, approach it thoroughly, and contribute by integrating updated information on a field that is still "sailing" on unchartered waters.

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It doesn't matter how beautiful your theory is, it doesn't matter how smart you are. If it doesn't agree with experiment, it's wrong.

Richard Feynman

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Introduction

The development of innovative technologies during the last decade has facilitated many aspects of people's lives via the interaction they have with them. More precisely, the implementation of artificial intelligence and machine learning techniques in many industries boosted their production and product and service efficiency and highlighted new opportunities arising from data-driven decision-making. Artificial Intelligence (AI) reduces human error and reaches, in most cases, the desirable accuracy. Though, it is imperative to provide the AI framework with the appropriate data.

AI contributes along with big data, robotics, IoT (Internet of Things), genetic engineering, quantum computing, blockchain, Web3, VR and AR digital experiences, and other technologies in the Fourth Industrial Revolution (4IR). The 4IR is developing exponentially bringing transformative changes in society and affecting almost every country's industrial sector. The adoption of AI has more than doubled between 2017 and 2022, whereas the average number of AI capabilities that organizations use, such as natural-language generation (NLG) and computer vision, have also doubled according to Mckinsey & Company (2022).

This Master's Thesis elaborates on the implementation of AI in pricing software and on the latest literature focusing on competition distortions arising from the use of AI pricing algorithms. Algorithmic pricing is commonly used by sellers in the digital marketplace. Latest years' introduction of reinforcement learning algorithms in pricing procedures has been noticed to deliver significant profits to sellers. Moreover, improved demand prediction ability is said to benefit consumers' welfare. In parallel, algorithmic pricing provides a certain level of price discrimination that in accordance with the rapid adaptability of prices in demand and/or supply fluctuations is considered to lead to a market's efficiency.

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In **Chapter 1**, I profile the technical elements framing algorithmic pricing and thus I analyze the notions of Artificial Intelligence, Machine Learning, and Algorithms as well as the latest extensions of machine learning techniques that provide autonomous action. Special attention is given to the base of the Q-learning method, i.e. the Bellman Equation. **Chapter 2** focuses on the field of pricing as a distinct area of industrial organization. This chapter elaborates on the notions of dynamic pricing and the origins of algorithmic pricing in digital markets, refers to the markets that are more likely to incorporate algorithmic pricing techniques as an asset of management and maps the kinds of algorithmic pricing that someone can find mostly in digital markets.

A broad analysis of the concerns regarding competition implications when digital markets use algorithmic pricing can be found in **Chapter 3**. Presenting the theoretical risks accompanying ML methods, as well as simple strategies that can be used to achieve collusive outcomes, is to set a solid base to step towards specific implications of competition. Thus, it is given a taxonomy of schemes that harm competition as well as recorded antitrust cases on both sides of the Atlantic. The main problem, that literature observes, is that algorithms (agents) act rationally and are able to learn collusive strategies by experimenting in a repeated game environment in the digital marketplace. In **Chapter 4**, someone can find the mechanisms behind the algorithmic tacit collusion and the markets that are more susceptible to these practices.

The literature review in **Chapter 5** attempts to present a rigorous collection of trending scientific papers coping with the problem of algorithmic coordination using sophisticated algorithms. The studies test pricing algorithms under various conditions changing the parameters of the underlying competition models and checking for robustness in order to present valid results. Most of the papers present experimental work and only one delivers an

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empirical study, a fact considered representative of the difficulty the antitrust authorities face if they have to detect tacit algorithmic collusion.

Chapter 6 presents the international policy context on artificial intelligence but first cites, in a distinct section, the issue of the Ethics of AI that has been much talked about in international and national fora in recent years. Further in the chapter, there are analyses of institutional approaches in AI classified according to geopolitical areas. First, there is Europe's approach and more precisely, the European Union's. The EU has paved a long way so far in Data management and AI policies, being the first to regulate AI on a global scale. Second, there is a presentation of the developments of AI in the United States of America. Third, I present Asia, and more precisely China's approach to AI, the most competitive area in AI developments worldwide, and the fourth section deals with international organizations' actions on AI in general. Finally, in the last section, the concluding remarks of the aforementioned extensive analysis of the trending topic of AI pricing algorithms are presented.

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CHAPTER 1_The Artificial Intelligence Algorithmic Pricing Concept

1.1. Artificial intelligence definition

Artificial intelligence (AI) is the term explaining the ability of a machine to successfully reproduce human-like cognitive capabilities. In fact, an exact definition of "intelligence" is hard to clearly state due to its vague concept, both in machines and in humans. So far, "intelligence" has been studied by psychologists, biologists, neuroscientists, and from a philosophical point of view as well. Among others, it is stated, but it is still a subject of research, that intelligence exists in part by virtue of our individual genetic inheritance. Though, it is a common perception that "intelligence" is a process incorporating autonomy and links with the ability *to cope with unpredictable circumstances* (MacFarlane, 2013).

Both arguments have a specific and generic appliance as they are both used for dealing with, not only concrete tasks, but it happens to govern human intelligence as a total, and thus the human reaction to any possible circumstance. For example, when humans deal with the secrecy of sensitive information, may use their experience, ethics, life purpose and other cognitive correlates as intention, perception, motivation, emotions, and implicit and explicit knowledge (Naseem et al, 2022). In the AI world, this relates with Artificial General Intelligence (AGI) or Strong AI where its conquest, by extension, relates to a state where AI surpasses human intelligence. Despite the significant progress in the field, results show that we are still far from it (Marcus, 2019), whereas relevant ethical issues arise at the same time.

AI researchers prefer to use the word "rationality". This is to depict "intelligence" mainly referring to the ability to choose the best actions, under certain criteria and available resources (Bounded Rationality) like time and computational power, in order to achieve the goal in

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demand (European Commission, 2019). Reasoning, learning, planning, and creativity are perceived as the "intelligent" behavior created artificially after successfully processing data. Though, rationality is not the only characteristic of an advanced AI system. An advanced AI system is a learning rational system. *A Learning rational system is a rational system that, after taking an action, evaluates the new state of the environment (through perception) to determine how successful its action was, and then adapts its reasoning rules and decision-making methods* (European Commission, 2019).

The European Commission in the Communication for Artificial Intelligence for Europe (European Commission, 2018) gives the following explanatory definition of AI: "Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications)".

An updated version of the AI definition is presented in the "Proposal for a regulation laying down rules on AI" by the European Commission in 2021. According to this, "Artificial intelligence is a fast-evolving family of technologies that can contribute to a wide array of economic and societal benefits across the entire spectrum of industries and social activities. By improving prediction, optimizing operations and resource allocation, and personalizing digital solutions available for individuals and organizations, the use of artificial intelligence can provide key competitive advantages to companies and support socially and environmentally beneficial outcomes, for example in healthcare, farming, education and training, infrastructure management, energy, transport and logistics, public services, security, justice, resource and energy efficiency, and climate change mitigation and adaptation. At the same time, depending

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on the circumstances regarding its specific application and use, artificial intelligence may generate risks and cause harm to public interests and rights that are protected by Union law. Such harm might be material or immaterial".

1.2. Data on the AI system

The AI systems are based on data and algorithms. By processing data, AI systems analyze previous actions and thus enhance their ability to adapt their behavior and respond effectively (human-like) in future likesome situations. This is the reason why they succeed in combinatorial problems like playing chess, but also in other tasks performing a human level result as an output of human judgment. Alan Turing set that as "learning from experience" or the ability to distinguish right from wrong (Russell et al., 2010).

The basic building blocks of an AI system are three. First, data input into the system. Second, the Reasoning/ Information process module takes place and third, the actuation phase completes the task. Data act as a fuel for AI. When data are provided for analysis, they are either already prepared or gathered through the machine's own sensors. Sensors' form can be input devices (e.g. cameras, microphones) or sensors of physical quantities (e.g. pressure, temperature). Internet expansion has further boosted AI due to the growing volume of data gathered in this environment. Sentiment analysis, for example, takes advantage of this data-blooming by recently using deep learning. Sentiment analysis (opinion mining) is the computational study of peoples' opinions, sentiments, emotions, appraisals, and attitudes towards entities like a service or product, organizations, individuals, events, and topics and has spread from computer science to management and social sciences (Liu, 2015). *For the first time in human history, we have a huge volume of opinionated data recorded in digital forms* (Zhang et al., 2018).

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What an AI system is capable of, depends on the AI techniques it incorporates. These techniques can be grouped into two main capability directions, Reasoning -Decision Making and Learning. A third discipline, Robotics, is a distinct but relevant area (European Commission, 2019). In the Reasoning/Information (R/I) process module, data are transformed into information that this module can understand (data modeling). Then, the AI system either reasons on this information/knowledge, i.e. by making inferences through symbolic rules, planning and scheduling activities, searching through a large solution set and optimizing among all possible solutions to a problem, or processing them. These tasks are performed by an algorithm.

1.3. The Consisting Elements of Artificial Intelligence

1.3.1. Algorithms

What an algorithm really is, is much more defined intuitively than being able to state one universally accepted definition, since the problem of defining algorithms is mathematically challenging, regarding Moschovakis (2001). Describing an algorithm intuitively, we can present it as a body or ensemble of fine-structured successive logic rules performing a certain result given a certain input (OECD, 2017). This special AI arm incorporates a group of techniques such as machine learning, neural networks, deep learning, decision trees, clustering methods, matrix factorization etc.

1.3.2. Machine Learning

Machine learning (ML), one of the tools of AI, is a subdivision of computational science that progressed from the learning of data classification based on the gained understanding and also from the learning gained on computational-based principles of AI (Vinoth & Datta, 2022).

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Consequently, ML refers to computational methods using knowledge -"experience" from past information in order to improve performance or to make accurate predictions. In order to perform such tasks, ML has specific content. Thus, ML consists of designing efficient and accurate prediction algorithms (Mohri et al., 2018).

A group of widely used ML tasks is the a) Classification of data, b) Regression to tackle the problem of predicting real values for e.g. stock values or variations of economic variables, c) Ranking according to some criterion, d) Clustering in order to partition a set of items into homogeneous subsets and e) Dimensionality reduction or Manifold learning.

Common ML scenarios comprise Supervised Learning, Unsupervised Learning, Semi-supervised Learning, Transductive Inference[1], On-line Learning, Reinforcement Learning and Active Learning (Mohri et al., 2018). Though, the most popular ML approaches are a) the Supervised, b) the Unsupervised and c) the Reinforcement Learning. ML scenarios differ in the types of available training data, the order and the method used to acquire those data and at last in the test data the learning algorithm used.

In Supervised Learning, the training data are already labeled and are provided to the system in order to make relevant predictions. In Unsupervised learning, the system receives exclusively unlabeled training data in order to make predictions for all unseen points (Mohri et al., 2018). In Reinforcement Learning, the training and testing phases are intermixed. In that scenario, the system interacts with the environment and in some cases affects the environment. For each interaction, the learning system is rewarded immediately on the basis of the action it made on the very last trial. Because of the particularity of the absence of long-term reward feedback, the

1 Transductive inference is reasoning from observed, specific (training) cases to specific (test) cases (https://www.cs.bham.ac.uk/~jdk/transductive.html)

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system faces the exploration-exploitation dilemma. This is to decide whether to proceed to unknown actions in order to gain information or exploit the information already collected.

ML though faces some fundamental questions regarding the extent to which it can be applied or efficiently process and perform wishful tasks. According to Mohri et al. (2018), these questions include "Which concept classes can actually be learned, and under what conditions?'' and "How well can these concepts be learned computationally?". The Probably Approximately Correct (PAC) learning framework helps to answer questions on learnable concepts linked to sample complexity and the time and space complexity of the learning algorithm (Mohri et al., 2018)[2].

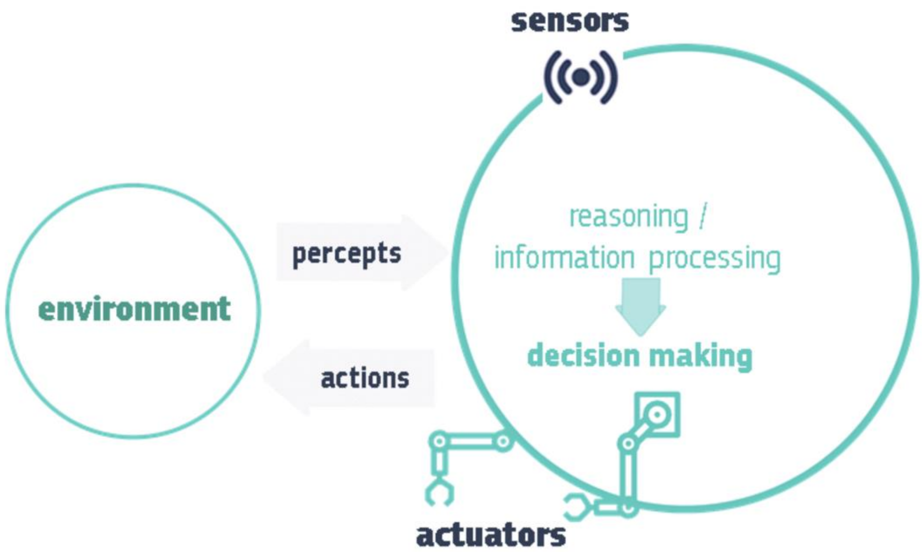

Figure 1 A schematic depiction of an AI system as it is published in EC Communication for AI (European Commission, 2018)

[2] The time and space complexity of the learning algorithm depends on the cost of the computational representation of the concepts. --Foundations of Machine Learning, Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar, MIT Press, Second Edition, 2018.

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AI technologies' importance is undiscussable and proved in many, if not all, sectors of life. Worldwide, AI is highlighted as a distinctive policy area that gains the public and private sectors' interest at an increasing rate. In Europe, the European Union recognizes the importance of AI and sets it as an EU priority (European Parliament, 2019) in order to enhance society's digital transformation but also prevent citizens from AI's usage dystopias. In the EU internal market, consumers' protection from AI technologies' unfair and discriminatory commercial practices is set as a policy target (European Parliament, 2020) with the new EU data-sharing legislation aiming to build trust in data sharing field while boosting data sharing in the EU (European Parliament, 2022).

1.3.3. Deep Learning

Deep learning has become the dominant approach to AI. It is a subfield of ML and aims to replicate the human brain's processing of information. It is based on a neural network, and more specifically an Artificial Neural Network (ANN) which is a set of algorithms incorporating mathematical formulas. ANN simulates the human neuron system and is enriched with three or more layers (IBM, 2020) in order to refine the learning procedure and conclude to valuable, safe, and accurate results like predictions, decisions, or actions. Although single-layer neural networks can provide approximate predictions, adding supplementary hidden layers contributes to further refinement and optimization. Thus, depth in this learning procedure refers to the many layers of a neural network, though, the absolute key aspect of deep learning is that these layers are not designed by human engineers but are learned from data using a general-purpose learning procedure (LeCun et al., 2015).

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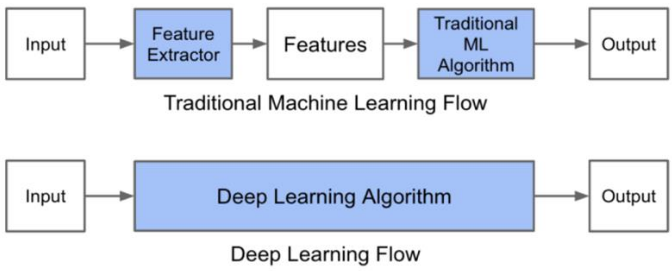

Figure 2 **Machine VS Deep Learning Algorithm** (OECD, 2017)

1.3.3.2. Deep Learning Algorithms and Neural Networks

Deep learning algorithms drive AI applications to high-end results without human intervention. At a very basic level, the algebraic formula is similar to linear regression as we observe below, but there is a significant difference that distinguishes regression from neural networks. Changing a weight in the regression does not affect the other inputs of the function. On the contrary, in the neural network, a single change in a weight, in one layer's output, ignites a domino of changes in the other neurons of the network.

The neural network formula comprises four main components: inputs, weights, a bias (/threshold), and an output. Weights assign importance to each input. Larger weights on an input define that this input's contribution to the output is more significant. Each formula is linked to an activation function that acts like an ignitor. If the formula's output surpasses a defined threshold value, then that node activates and sends data to the next neural network layer.

$$\text{output} = f(x) = \begin{cases} 1 \text{ if } \sum w_1 x_1 + b \geq 0 \\ 0 \text{ if } \sum w_1 x_1 + b < 0 \end{cases}$$

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Each neural network tends to have multiple hidden layers that repeat the same procedure but the activation function differs from layer to layer. After all outputs from all layers are extracted, they are used as inputs for the final result/output. Although the aforementioned process is characterized by linearity, real-world conditions are complex and non-linear.

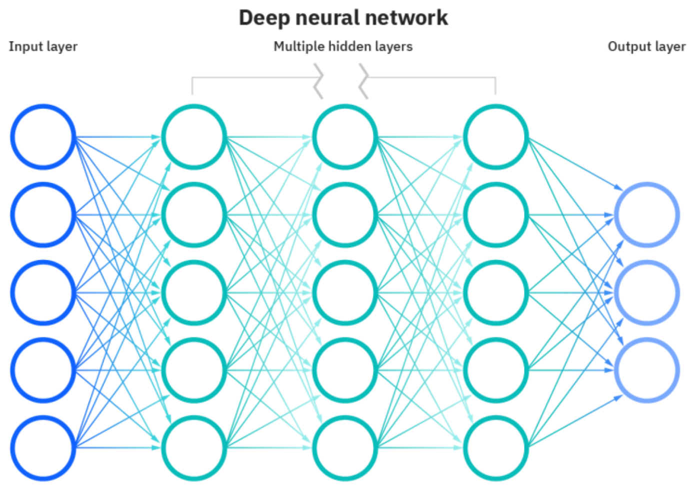

Figure 3 **A Deep Neural Network (Source:https://www.ibm.com/cloud/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks**

1.3.3.1. Training a Deep Neural Network

The training of a deep neural network may be realized feed-forward (forward propagation) and supplementary through backpropagation. In forward propagation, training flows in one direction gradually from input to output. The backpropagation procedure exploits the error in each neuron. More precisely, backpropagation uses algorithms like Gradient Descent to calculate errors in predictions and then adjusts weights and biases in the function by moving backwards through the layers in order to train the model. Through both forward and back-propagation the algorithm becomes more accurate (IBM, 2020).

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1.3.3.2. Subcategories of Deep Learning (RL) algorithms

In the field of deep reinforcement learning (RL) algorithms, there are two broad categories, a) model-based RL algorithms (here the agent has access to the transition probabilities and the reward functions) and b) model-free RL algorithms (here the agent interacts directly with the environment and learns actions when there is a better reward). According to the literature, model-based RL algorithms work well due to that they allow the agent to plan ahead in a strategic way considering future awards and transitions. Nevertheless, when there is a problem with high dimensional state space and continuous action space such as the toll pricing problem, it is difficult for the algorithm to plan over all possible future states and actions. This is the reason for turning to model-free RL methods (Pandey et al, 2020).

Model-free RL algorithms include two more subcategories based on the characteristic of the Markov Decision Process they learn from interactions with the environment. The subcategories include the value-based methods and the policy-based methods. The first try to learn the value functions using approaches based on dynamic programming in order to solve the problem. Deep Q-learning (DQ Network) belongs to that category and is the most popular value-based method. In DQN the function approximators for value functions are replaced by neural networks. A further subdivision is observed in the Deep RL algorithms. These are further divided into on-policy and off-policy algorithms. This classification arises from the way agents' experiences are used to learn better policies.

On-policy algorithms learn the value of the policy as the agent operates taking actions and then uses the learned values directly for controlling and thus improving the policy. The off-policy algorithms improve the policy by using data collected across different past interactions and that makes this algorithm more efficient. Consequently, on of the most popular off-policy algorithms is the Deep Q-learning with Experience Replay. The second type of methods, the policy-based, try to learn the policy directly based on observations and operate well under

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continuous state and action spaces, being the preferred choice for the toll optimization problem (Pandey et al, 2020).

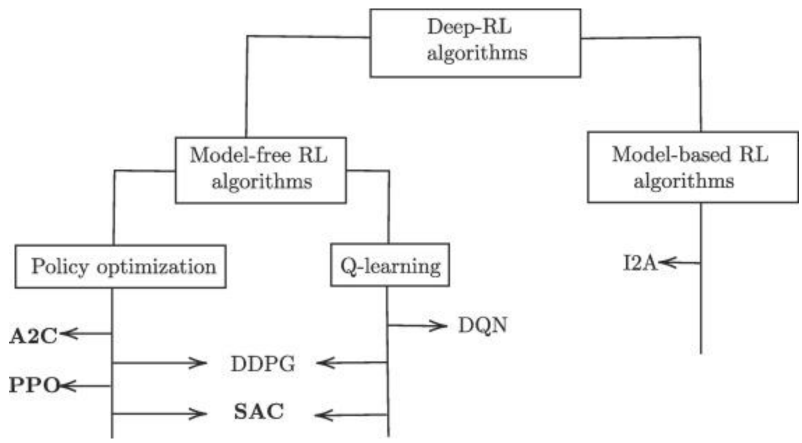

Figure 4 Partial taxonomy of RL algorithms in the literature (Pandey et al, 2020)

1.3.4. Q-learning

Q-Learning is a type of reinforcement learning but it is model-free. Q-Learning finds the best action given the current state/environment of the agent. According to Watkins and Dayan (1992), it can be viewed as a method of asynchronous dynamic programming (DP) proceeding similarly to Sutton's (1984;1988) method of temporal differences[3]. Q-learning allows agents to learn to act optimally in Markovian domains by experiencing the consequences of actions, without requiring them to build maps of the domains. In general, Q-learning tools manage to find an optimal policy in MDPs (Markovian Decision Problems) or similar to these. *An MDP is a formal framework that analyze repeated decision-making in dynamic and stochastic*

[3] Temporal Differences (TD): An agent tries an action at a particular state, and evaluates its consequences in terms of the immediate reward or penalty it receives and its estimate of the value of the state to which it is taken. By trying all actions in all states repeatedly, it learns which are the best overall, judged by long-term discounted reward. Watkins, C.J.C.H., Dayan, P. Q-learning. Mach Learn 8, 279–292 (1992). https://doi.org/10.1007/BF00992698

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environments (Calvano et al., 2019). Watkins (1989) characterizes the Q-learning method as incremental dynamic programming due to the step-by-step manner in which it determines the optimal policy.

1.3.4.1. The Bellman Equation as part of the Q-Learning Algorithm

The goal of Q-learning is to estimate Q values in order to achieve optimal policy. The overall technique is built up on the Bellman equation formed as we observe below.

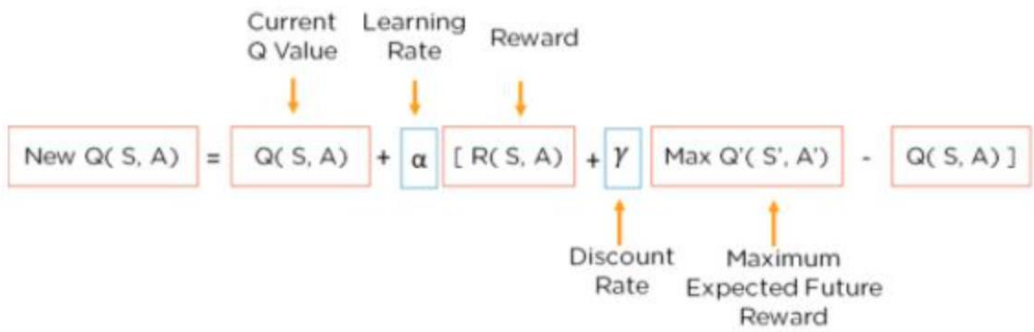

Figure 5 The Bellman Equation (Source: https://www.simplilearn.com/tutorials/machine-learning-tutorial/what-is-q-learning).

At this point, it is important to state the elements consisting the Bellman equation and the Q-learning method following Watkins and Dayan (1992) approach. The environment ("world") in which the agent acts, is a controlled Markov process and the agent is the controller. At step n the agent is capable to register the state x_n ($\in$ X) of the "world" according to which chooses its action a_n ($\in \Re$). For that action, the agent receives a probabilistic reward r_n, *whose mean value* $Rx_n(a_n)$ solely depends on the state and the action. The state of the "world" changes probabilistically to y_n according to the following law:

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Prob $[y_n = y|x_n, a_n] = P_{x_n y}[a_n]$

As we mentioned above, the agent's target is to determine an optimal policy π*. We refer to an optimal policy in an indefinite way because there may be more than one optimal policy. Though, Q* values are unique. An optimal policy is one that maximizes the total expected reward discounted by a factor γ^s with $(0 < \gamma < 1)$ and s representing time-steps forward/future rewards. Thus, under a policy π, the value of state x is :

$$\boxed{V^{\pi}(x) \equiv R_x(\pi(x)) + \gamma \sum_{y} P_{xy}[\pi(x)]\, V^{\pi}(y)}$$

The agent expects to receive $R_x(\pi(x))$ immediately after performing the action that policy π recommends. Then, the agent, with probability $P_{xy}[\pi(x)]$ segues into a state that is "worth" $V^{\pi}(y)$ to her. According to Dynamic Programming theory, there is at least one optimal stationary policy π* for an agent at a state x where we have that

$$\boxed{V^*(x) \equiv V^{\pi^*}(x) = \max_{a} \left\{ R_x(a) + \gamma \sum_{y} P_{xy}[a]\, V^{\pi^*}(y) \right\}}$$

for which there are also provided a number of methods for calculating V* and one π*, given $R_x(a)$ and $P_{xy}[a]$. Though, the peculiarity a Q-learner faces, is to determine π* without initially knowing the aforementioned values. Although there are traditional methods for specifying $R_x(a)$ and $P_{xy}[a]$, the authors support that any assumption of certainty equivalence (ie calculating actions as if the current model were accurate) costs dearly in the early stages of learning (Watkins & Dayan, 1992).

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A policy π determines an action α, thus Q values can be as well viewed as action-values. Consequently, defining Q values we have that

$$Q^{\pi}(x, \alpha) \; = \; R_x(a) \; + \; \gamma \sum_y P_{xy}[\pi(x)] \, V^{\pi}(y)$$

We observe that the Q value is the expected discounted reward for executing action α at state x and following policy π thereafter (Watkins & Dayan, 1992).

We then define $Q^*(x, \alpha) \equiv Q^{\pi^*}(x, \alpha)$, $\forall$ x, α as the optimal Q-value. We consequently have that $V^*(x) = \max_{\alpha} Q^*(x, \alpha)$ and if α^* is an action through which we attain the maximum, we straightforward form the optimal policy as $\pi^*(x) \equiv \alpha^*$. This is the key element of the usefulness of Q-values. Since the agent learns these values, she can effortlessly decide what is optimal to do. The experience the agent builds is gained through a sequence of distinct stages or episodes in the Q-learning method. More explicitly, in the n^th episode the agent:

- Observes its current state x_n
- Selects and performs an action a_n
- Observes the subsequent state y_n
- Receives an immediate payoff r_n and
- Adjusts its Q_{n-1} values using a learning factor α_n according to the following formula, assuming initial Q_0 values as given:

$$Q_n(x, \alpha) = \begin{cases} (1-\alpha_n)Q_{n-1}(x, \alpha) + \alpha_n[r_n + \gamma V_{n-1}(y_n)] & \text{if } x = x_n \text{ and } \alpha = \alpha_n \\ Q_{n-1}(x, \alpha) & \text{otherwise} \end{cases}$$

where $V_{n-1}(y) \equiv \max_b \{ Q_{n-1}(y, b) \}$ is the best the agent thinks can do from state y.

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Each episode's calculations assume a Q-table (Q-matrix), a table mirroring the results of rewards and Q-values to any action taken. This look-up table contributes to detecting the best action in each state in the environment. Q-learning is at its core the method for the estimation of the Q-matrix without having knowledge of the underlying model, i.e. the probability distribution function (Calvano et al.,2020).

According to the convergence theorem the authors deploy, as $n \rightarrow \infty$ $Q_n(x, \alpha) \rightarrow Q^*(x, \alpha)$ under a defined set of conditions. The most important condition for the convergence towards the optimal policy is that the sequence of episodes that forms the basis of learning must include an infinite number of episodes for each starting state and action. Although this is considered a strong condition for how states and actions are selected, under the stochastic conditions of the theorem no weaker conditions may lead to the optimal policy (Watkins & Dayan, 1992).

1.3.4.2. The Popularity of Q-Learning Algorithms in Literature

Q-learning algorithms are popular because of a number of reasons. First, they do not need to be trained with data but they achieve the optimal policy by "playing" and, thus, are ready to "fight" in the market battlefield. Second, they do not require to prespecify a rival's future reactions to a special price setting. Third, they can manage uncertainty and operate under very little information. Much of the literature regarding the use of Q-learning algorithms in digital marketplaces chooses that kind of algorithm to test because of a) its popularity among computer scientists, b) its simplicity, which leads to economic interpretation clarity, although its learning process is slow, and c) has the same architecture as the more highly sophisticated programs that have recently reached impressive results (Calvano et al., 2020).

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1.3.5. The Deep Q-Network

When a non-linear function approximator like a Neural Network is used to represent the action-value function (Q-function), it is *known* to diverge or be unstable (Mnih et al., 2015). This challenge is solved through the pioneering work presented in Mnih et al. (2015) paper. The Google DeepMind team created a novel artificial agent, named Deep Q-Network (DQN) that achieves stability via experience replay. In DQN, the trajectory of the Markov Decision Process is stored in a replay memory and at each iteration, the Q-Network is trained via observations consisting of a sample of states, actions, rewards and next states extracted from the replay memory.

An approximation of the action-value function is already achieved and the DQN method proceeds to its second stage where another neural network characterized as the *target network* is used to obtain an unbiased estimator of the mean-squared Bellman error which is used to train the Q-network (Fan et al., 2020). DQN's particularity lies in its "ability" to *learn successful policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning and thus be able of learning to excel at a diverse array of challenging tasks.*

CHAPTER 2_Pricing

2.1. Algorithmic Pricing and Digital Markets

Firms have started exploiting the dynamics of technology and artificial intelligence advancements in business management. It is since the 1980s, with the deregulation of airline pricing in the US Airlines industry that dynamically adjusted pricing was launched on American Airlines by its president Robert Crandall (McAfee & Te Velde, 2006). Dynamic pricing or algorithmic pricing lies at the intersection of statistical learning - regarding estimations of demand, supply and current market conditions- and price optimization (den Boer, 2015).

The use of software that provides algorithmic pricing has initialized a new era for digital markets and competition. Several industries nowadays price consistently via dynamic pricing algorithms and experience a significant increase in profitability, while more and more invest in pricing technologies. The industries that currently implement dynamic pricing methods include airlines, hospitality, car rental, retail, e-commerce, automotive parts commerce, sports teams tickets and the Utility industry like water and electricity. The success of dynamic pricing algorithms is due to its combination with artificial intelligence and machine learning which further boost the optimality of this pricing procedure.

Algorithmic pricing with the use of AI and ML takes into account company's specific characteristics and strategy, and evaluates historical data, market trends and customer behavior to provide a profit-maximizing price. Despite that historical data, consumer behavior and market trend constitute commonplace for any company using the same pricing techniques (i.e. AIA pricing), a firm's specific strategy accounts for a blind point since it is about private sensitive commercial information. The aforementioned elements related to this tool's

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implementation give rise to challenges that businesses and competition authorities have to confront hereafter. Nevertheless, it is stated that the competitive effects of algorithmic pricing will become only more important as they are increasingly adopted in a wide array of markets (Brown & Mackay, 2022).

The digital market on its whole has emerged and built its reputation on early characteristics that have yet become expectations by consumers for a fairer market with higher competition, lower prices, an assortment of unlimited choices, a better view of a product's price range among multiple sellers, easiness of the purchasing procedure with less effort and saving time for other duties dealing successfully with the pressing dynamics of daily life. A condition like this, undeniably makes markets more efficient and benefits consumers in multiple ways capitalizing also opportunity cost. Nevertheless, this is only partially realized since a few retailers dominate online markets (Brown & Mackay, 2022).

2.2. Firms incorporating AIA pricing

World top firms are recorded as exemplary cases of the use of AI algorithmic pricing. Amazon.com Inc, the American multinational e-commerce company successfully implements dynamic pricing strategies. The company charges products at competitive prices and puts pressure on retailers linked to their varying sizes and popularity. With a periodic change in prices every ten minutes and the charge of a different price between the selection of the product and the final step of the completion of the purchase, this strategy has given rise to Amazon's profits by 25% (Mehta N., 2018). Amazon takes advantage of its own gathered big data (more than one billion gigabytes of data) and AI and ML advancements to calculate customer's purchase patterns, profit margins, competitors' prices within the platform as well as other data

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in order to provide a competitive price in common products undercutting its competitors (remi.ai, 2020).

Uber is another American company providing ride-sharing services and makes use of surge pricing ie charges more for a service when it is in high demand. Uber acts in a market under fluctuating demand and variable supply of drivers/partners because of the particularity of the partnership which allows drivers to provide service whenever they want to. In that case, when it happens that riders surpass available drivers, it has to give incentives to more of the last to provide their services. Uber's surge pricing algorithm assigns a multiplier to the regular fare increasing the ride price and with that attempts to close the gap between demand and supply (Hall et al., 2015). Real-time data such as traffic and weather are used in the evaluation process.

Airbnb, the popular home rental marketplace makes use of dynamic pricing algorithms but acts only as a platform for third-party hosts. Airbnb's pricing adjusts prices within a threshold chosen by the host and even if the latter doesn't make use of the Smart Pricing tool, the platform can still make price recommendations (remi.ai,2020) to her.

More and more companies in the digital market use AI dynamic pricing to enhance their profits by being up to date on rivals' pricing policies, consumers' preferences, and market trends. Though, in order to implement AI dynamic pricing in a company, there is a need to secure certain prerequisites. Small companies for example have difficulties in finding resources to implement dynamic pricing or larger ones may have complex deals or not appropriate data. A third barrier appears to be customers' refusal to accept dynamic pricing implementation (Shartsis, 2019).

The corresponding pricing software is considered an asset for the company that incorporates it into the management structure, as it fulfills the requirements for profit maximization. The

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aforementioned kinds of markets applying algorithmic pricing share some common characteristics that can be summarized as follows, according to Oxera (2017):

A) *the costs to serve consumers differ considerably from consumer to consumer, in ways which can be approximated using observable data (e.g. credit and insurance markets);*

B) *demand fluctuates much more rapidly than supply (e.g. hotels and ride-sharing); or*

C) *the price-setter has a wide range of products to price, and algorithmic approaches bring a significant cost advantage (e.g. consumer retail).*

There may be customized algorithmic pricing software solutions for a company that can afford that, entailing special design based on the company's life vein (i.e. prices, products, costs, stock, market demand and production flow if it is the case), elements that can be proved quite costly. On the other hand, there are off-the-shelf pricing solutions through SaaS (Software as a Service). In both cases, if the pricing algorithm is AI-powered, meaning a deep-learning base, the company may face undesirable outcomes due to the "black-box" part of the deep neural network.

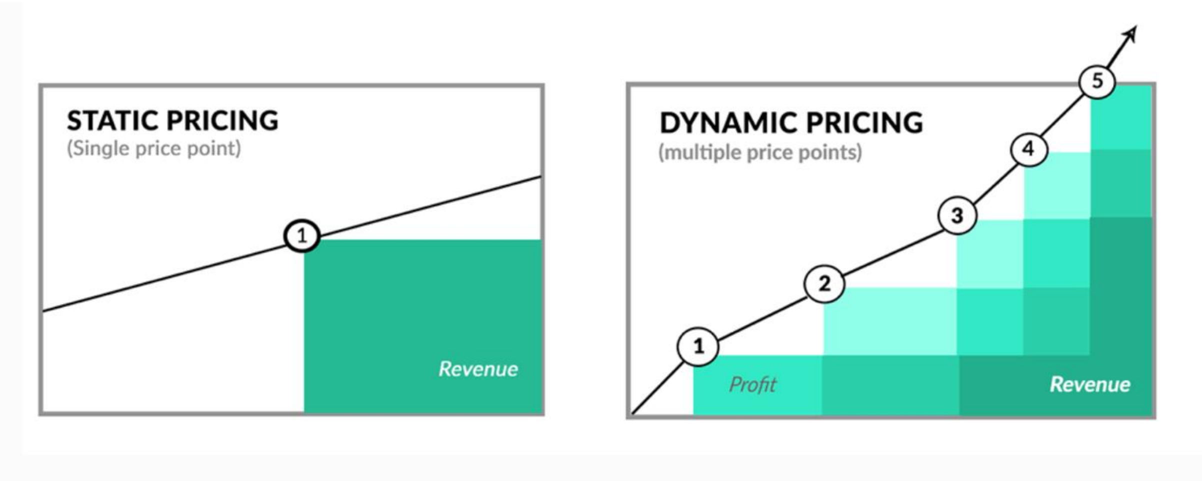

Figure 6 **Static Pricing VS Dynamic Pricing (Source: https://competitoor.com/dynamic-pricing-how-works/)**

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Algorithmic Pricing is considered to be beneficial in many aspects of current and future markets. Prices change and adjust fast to variant market conditions, like changing costs and demand shocks. The platforms that use algorithms achieve clearing of the markets worldwide, especially when the platform collects detailed data about the demand and supply, meaning an informational advantage for the platform operator. AP may also contribute to cost reductions by eliminating staff involvement in the pricing procedures of a company. At the same time, AP lowers barriers to entry by breaking the wall of specific market knowledge in order to enter the market and consequently set prices. This mechanism also gives retailers the opportunity to broaden their group of products and add kinds in which they do not have expertise.

Literature gives prominence to both sides of this controversial though effectual asset. Where some experts reassure that there is no reason for competition authorities to pay special attention to the issue (provided that future prices remain competitive), others boldly underline the risks for consumers and society. Indeed, AP may intensify competition, considering the fast responses between competitors which will lead, as well faster, to a competitive outcome. On the other side, AP occupies antitrust authorities' attention due to extended anticompetitive outcomes that may occur.

2.3. Dynamic Pricing origin and characteristics

Dynamic pricing is as old as commerce itself (Talluri and van Ryzin, 2004) and can be the best technique used for revenue management in several product categories (Stasinski, 2020). Dynamic pricing and revenue management are certainly related fields. In the 1970's, some airline companies started to offer restricted discount fare products mixing discount and higher fare passengers in the same aircraft compartments. This was an innovation at that time, offering the airline the potential to gain *revenue from seats that would have otherwise been empty* on a

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certain flight. It can be stated that only quite later *in 1999, most of the world's major air carriers and many smaller airlines have some level of revenue management capability* (McGill and van Ryzin, 1999). Consequently, such fare price adjustments are *welfare improving as they increase capacity utilization* (Williams, 2022).

Revenue management is perceived as inventory control from an organization's point of view and when it turns to forecast, it embraces a product archetype with a focus on estimating demand by class. On the other hand, dynamic pricing models treat price as a variable and typically focus directly on the price and demand relationship (Boyd and Bilegan, 2003) dealing with the determination of optimal pricing policy for products and services and serving as *a special form of demand response, allowing better optimization of resource utilization.* Additionally, it can be used as a demand-shaping mechanism when goods and services have a price-dependent nature (Stasinski, 2020). In this section, it will be followed, in general, Stasinski's (2020) literature review approach and facts stated in her work relevant to dynamic pricing.

Dynamic pricing is linked to two problems, a) demand estimation and 2) understanding the demand-price relation, which will allow for price forecasting and relation shaping. Digital technology's development has made it possible for several businesses to adopt dynamic pricing, and more precisely algorithmic pricing techniques, as an indispensable part of their pricing policies. On the problem of demand estimation, it is Charles Davenant, almost three decades ago, who first identified demand curves, relating the supply and price of corn (King-Davenant Law). That is considered the first known empirical work on demand curves. Later at the beginning of the 20th century, more advanced research emerged on estimating demand curves using statistical techniques such as correlation and linear regression (den Boer, 2015). Though, the demand curves estimation of various products, according to den Boer (2015), was not for

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the purpose of commercial firms' profit maximization. They were rather used to support macroeconomic theory on price, supply, and demand.

Demand is estimated using certain techniques. The most popular demand estimation models are the a) stochastic models, b) fuzzy logic models, c) action-set models, and d) learning models. The stochastic demand models are probabilistic models. They are the most popular regarding demand estimation and have been used in energy consumption, routing, deteriorating stock management, and in general dynamic pricing model evaluation. Fuzzy logic models, also called fuzzy sets, process vague and imprecise information. Action-set models are event-based models relying on a set of predefined reactions to market changes. Finally, Learning models (among which currently the most popular is reinforcement learning) are used to solve decision-making problems utilizing typically Markov Chain decision process although may as well use several environment definitions.

Price forecasting, the other problem of dynamic pricing, depends on the identified demand and on the considered inventory restrictions[4]. Cournot's "Researches into the Mathematical Principles of the Theory of Wealth" is acknowledged as the first source where the demand-price relation of products is defined as a mathematical function and thus solving the mathematical problem of the determination of the optimal selling price. Applying mathematical methods to study an economic problem was considered a new and controversial approach (den Boer, 2015). A representative statement has been displayed by Fisher, in 1898, in the abstract of his work mentioning that "Cournot's genius must give a new mental activity to everyone who passes through his hands".

[4] The vendor cannot sell wares that are not present in the inventory (Stasinski, 2020).

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As mentioned above, revenue management and dynamic pricing connect in some way. Revenue management's inventory control is as well a crucial part of dynamic pricing's design. More precisely, identifying inventory restrictions is important to define the pricing policy for dynamic pricing solutions. There are two research streams based on the inventory restrictions problem. The first stream focuses on the "inventory-procurement" problems which cover the limitations relevant to the inventory size and the expected sell-out time, i.e. considering the vendor has a *certain amount of products that need to be sold in a finite amount of time*. This problem can be further divided in two more problems, a) considering only a *fixed number of products during a finite time period* and b) *selling the maximum (sustainable) number of products during a finite time period*. Fisher et al (2018) study a competition-based dynamic pricing model with a fixed inventory. The findings show that a best-response pricing algorithm that takes into account consumer behavior, competitor actions, and supply parameters demonstrates a significant revenue improvement of 11% for the product category under study. Though, such improvement is not specific to this category only, according to the study. The second inventory limitations problem stream is about "revenue-quality management". This stream deals with the case that the *inventory value may decrease in time due to its quality or incurred utilization costs*. The vendor, here, faces a certain amount of perishable goods that need to be sold with the maximum revenue in a time-bounded selling horizon. The decaying interest of the clients is also included in this case.

Dynamic pricing is applied in many market branches such as airline companies, car rental, retail stores, the hospitality sector and internet advertisements (den Boer, 2015). In a broader view, and according to the papers elaborated by Stasinski (2020), it is applicable in the e-commerce and services sector (e.g. same-day delivery, ticket sales, car sharing, hotels and apartments, deteriorating stock management) and in power management (e.g. electric vehicles charging sustainability management, distributed energy management, load forecasting, smart

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grid management). Machine learning (ML) approaches are used to learn market dynamics and propose a pricing policy, allowing that way the model to achieve both demand estimation and price calculation into a single package. ML techniques that have been applied to dynamic pricing problems encompass reinforcement learning and Q-learning algorithms, Markov chain Monte Carlo methods, the aggregating algorithm, particle swarm optimization, simulated annealing, goal-directed and derivative-following strategies in simulation, neural networks and direct search methods (den Boer, 2015).

In addition, the use of behavior data (in pricing) reduces price competition even if consumers behave in a strategic manner (van der Rest et al, 2020), though according to relevant studies, dynamic pricing strategies can affect customers' *perceptions and behaviors in positive and negative ways*. The view of consumers on dynamic pricing varies depending on the industry, resource availability, personal circumstances, and on beliefs about the suppliers' fair acting. Nevertheless, consumers accept dynamic pricing if they understand the concept behind such as demand and supply (Neubert, 2022). Finally, a key assumption in dynamic pricing models has to do with the competition level the firm faces and thus there are a monopoly, oligopoly and perfect-competition models. For example, when using monopoly pricing models, the firm faces only a demand depending only on its own price rather than on the competitor's price. Although several risks occur regarding this approach, monopoly models are proved valuable for decision support (Talluri and van Ryzin, 2004).

2.4. Mapping Algorithmic Pricing

Oxera's (2017) discussion paper distinguishes four types of algorithmic pricing (AP). First, there is heuristic pricing, a software relying on simple rules and on the "state of the world", i.e. data, relevant to the market or e.g. the company's stock, feed the algorithm and this responds

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with a certain price. Second, there is the analytical AP which sets prices as well according to the "state of the world" but the pricing rule uses statistical methods to analyze historical data. Third, the autonomous AP prices according to the "state of the world" but has two special features, a) it is trained with historical data and b) updates its performance after evaluation on observed outcomes, contrary to the analytical AP which is static. The fourth AP software is categorized under the title "Auctions" as it implements auctions in the sales of ad spaces in websites and in retail sites e.g. eBay. The fourth type of AP is characterized as more transparent since market participants are aware of the mechanism that determines the price, contrary to the first three which are "take-it-or-leave-it offers". Notwithstanding, human intervention, in all 4 types, is considered an integral part of the AP mechanism in order to correct errors, ponder additional data and apply constraints in the algorithm e.g. minimum and maximum prices.

2.5. Pricing Algorithms Categorization

The algorithms used for pricing are classified into two categories, a) first-generation pricing algorithms and b) second-generation pricing algorithms. The first category of algorithms is *adaptive in nature*. They consist of a set of rules dictating optimal policies for specific contingencies. This was met in firms of the hotel booking and airline services class that used dynamic pricing in order to optimize revenue management. The adaptive algorithms rules have an estimation module and an optimization module. The estimation module is used to estimate market demand relying on previous sales volumes and prices. Potentially, it may include other control variables too. The estimation of demand and the observation of rivals' past behavior are then used to activate the second module, the optimization operation, which chooses the optimal price.

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Nevertheless, if the market conditions are known, then there is no need to activate the module of demand estimation. On the contrary, in that case, the adaptive algorithms' optimization module sets prices according to the past prices of the rival or in the even more sophisticated context of the rival's hypothetical strategies. In that category, we observe the following pricing strategies according to Calvano et al (2019): a) best response dynamics (the prices the firm chooses are the best response to the rival's last period prices), b) fictitious play (the firm chooses a price as the best response to an imaginary mixed strategy conceived as being the distribution of the past price) and c) Bayesian Learning (the firm plays a best response to a weighted average of past previous prices with exponentially declining weights).

The second-generation pricing algorithms are the learning algorithms that take advantage of computer science and belong in the fields of Artificial Intelligence and more precisely Machine Learning (ML). The ML algorithms experiment with what is called strategies i.e. actions deploying possibly suboptimal prices and then learning from the consequences. In the case of pricing algorithms, there is no specific model of the market included in the algorithm's design. They are model-free and the programmer intervenes only in the selection of the variables upon which the strategy should be conditioned, in the frequency of the experimentation stage of the program, and finally selects the weight that will be attributed to the *cumulative stock of knowledge* versus (/and to) the recently gained experience. The algorithm then plays optimally from experience. The Q-learning algorithms belong in this category (Calvano et al., 2019).

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CHAPTER 3_ AI Pricing and Competition

3.1. Competition Implications

The expansion of algorithmic pricing worldwide creates various implications for competition. More precisely, the issue that captures the attention of antitrust agencies is the algorithmic collusion that happens, according to the literature, while firms operate in digital markets and use algorithmic pricing methods. From the "competition" point of view, it is considered as unlikely that adaptive algorithms' programmers can achieve coordination without preceding explicit communication. In addition, such algorithmic pricing programs require *lines of coding*, and that can reveal the programmers' or even managers' intent to collusion. On the other side, according to the literature, the ML pricing algorithms learn not only to adapt to the rapidly changing market environment but also, they might learn how to cope with competitors and achieve profitable and sustainable collusion surpassing the coordination problems of achieving a collusive outcome and following retaliation mechanism (Calvano et al., 2019).

Moreover, the greater discussion on AI pricing algorithms has highlighted some theoretical risks linked to ML methods. These risks are articulated as follows, regarding the work of Beneke and Mackenrodt (2021):

> Clustering with unsupervised deep learning can be used to better segment customers and find those who seem to be more passive and therefore more susceptible to collusive prices; demand forecasting done by supervised learning algorithms can help firms to estimate demand elasticities more accurately and thus enable firms to better estimate the reservation price of certain customer groups; finally, through reinforcement learning, the method by which an algorithms learns from past data and by engaging in experimentation itself, firms can automate pricing strategies according to many variables such as reactions by competitors and the impact this has on the variable to be optimized, such as profits or market share. As these problem-

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solving capabilities improve, then market prices will tend to be more stable and converge to a level upwards of the competitive benchmark.

According to Varian Hal (2018), there are very simple strategies that can be used to facilitate collusion such as a) the Rapid Response Equilibrium (practices of this type may have been used in online competition e.g. airlines fare pricing and in the gas stations competition), b) the Repeated Prisoners Dilemma ("Under what conditions will cooperation emerge in a world of egoists without central authority?" stated Robert Axerlod in the introduction of his work "The Evolution of Cooperation" in 1984, where he conducted a prisoner's dilemma tournament· the winner was by a large margin a "tit-for-tat strategy"), and c) NASDAQ Price Quotes (in 1990 price quotes in the NASDAQ were made in eighths of a dollar rather than cents. Thus, if a bid was three-eighths and an ask was two-eighths then a transaction would occur with the buyer paying three-eighths and the seller taking two-eighths. The difference between the bid and the ask was the "inside spread," compensating the traders for risk-bearing and maintaining the necessary capital in order to participate in the market. Later, in the mid-1990s two economists, W. Christie and P. Schult highlighted *an understanding or implicit agreement among the market makers to avoid the use of odd-eighth price fractions when quoting these stocks*). All three practices align with Axerlod's "evolution of cooperation" meaning the occurrence of cooperation in the framework of repeated interaction.

3.2. Taxonomy of schemes harming competition

The concept of Algorithmic Tacit Collusion is different and difficult to detect. First, Ariel Ezrachi and Maurice E. Stucke raised specific concerns regarding algorithmic pricing and tacit collusion in 2015. In consecutive research papers, the law professors exemplified the concept of competition distortions and yet opened a great discussion on the subject till nowadays (2023).

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Ezrachi et Stucke (2015) present a taxonomy of the schemes where algorithms could end up harming competition by exhibiting collusive behavior without being explicitly programmed to achieve that. The classification is sketched on the algorithms' role in the price-setting process (Oxera, 2017). The schemes are:

a) Hub and Spoke
b) Predictable Agent
c) Autonomous Machine (Digital Eye)

i. Hub and Spoke

"Hub and Spoke" immediately gives us a sense of the structure of the scheme. Several competing firms, considered as spokes, delegate their pricing decision to the same provider of pricing software, the hub. The provider may as well be a SaaS i.e. a platform giving access to sellers to use their pricing software online. A "hub and spoke" may emerge when the "spokes" use the same algorithm or the same market data to determine the price. Under this framework, since the algorithm operates and interplays in the same digital environment, will conclude to same or similar prices i.e. to price parallelism. In spite of this, if communication between the client firms happens, we consider it as explicit collusion[5] and there would be no new competition law issues according to Gautier et al (2020). Competing firms, using the same algorithm, would result in displaying the same market behavior, as it resembles using *a similar*

[5] In that case, the "Messenger" scheme (another proposed category by A. Ezrachi and M. Stucke) would be valid. According to Ezrachi et Stucke (2017) [*Artificial intelligence & collusion: When computers inhibit competition. U. Ill. L. Rev., 1775.*], the "Messenger" category "concerns the use of computers to execute the will of humans in their quest to collude and restrict competition". Thus, "the legal concept of agreement can be applied straightforwardly" which is the case of US v. Topkins, US v. Aston and Trod and of the CMA Case 50223/2016, Online Sales of Posters and Frames, as mentioned in the previous section.

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"brain" to determine their price strategy. The "hub and spoke" coordination would be even more intensified if the algorithm uses the same data pool. Hence, this type of coordination can be observed either at the input level (same data) or the output level (same algorithm) (Ezrachi and Stucke, 2017).

ii. The Predictable Agent

The "Predictable Agent" is a more complex scenario than the previous one. The operator designs unilaterally the software and concludes with predictable outcomes. Furthermore, its reaction to changing market conditions is as well executed in a given way. Consequently, this pricing algorithm has limited ability to behave autonomously, i.e. autonomous learning and autonomous acting. The responses of the algorithm are based on hard-coded[6] rules, examples of which are the "win-continue lose-reverse" or "match low price/tit for tat" algorithms. Nevertheless, operators are aware of similar designs or relevant developments owned by their competitors. Thus, the industry-wide use of such software would result in anti-competitive outcomes through the creation of interdependent action (Ezrachi et Stucke, 2017). The "Predictable Agent" algorithm relies on a zero-determinant strategy in a framework of iterated prisoner's dilemma. In the zero-determinant strategy, it is possible to set unilaterally the rival's expected outcome. Though, this coordination's outcome is ambiguous as there is a potential risk for the algorithm to elude from reasonable updating of its own price as documented in the "Making of a Fly" textbook case in which the book's price hiked up to $23million (Gautier et al, 2020).

[6] **Hard-coded**. *Fix (data or parameters) in a program in such a way that they cannot be altered without modifying the program.* Source: Oxford Languages

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iii. The Digital Eye

The "Digital Eye" is the third category of price-setting algorithms, also referred as the "Autonomous Agent". The "Autonomous Agent" algorithms are designed to optimize the objective i.e. maximize the profit or minimize the loss. They are based on *sophisticated ML paradigms* (sic) and experiment to reach the optimal policy which satisfies the goal. This kind of algorithm is related to the latest technology developments and the fields of deep learning and neural networks applications. This scheme displays a *"higher degree of fit" with the notion of Tacit Collusion* (Gautier et al, 2020).

	Agreement	**Intent**	**Liability**
Category 1: *Messenger*	Strong evidence	Limited role	*Per Se* Illegal
Category 2: *Hub & Spoke*	Mixed evidence	Evidence used to clarify purpose and likely effect	*Per Se* / Rule of Reason
Category 3: *Predictable Agent*	No evidence	Evidence used to show motive and awareness in facilitating tacit collusion	Maybe under FTC Act § 5 or Article 102
Category 4: *Digital Eye*	No evidence	No evidence	Unclear

Figure 7 Categorization of the mechanisms that can be used to harm competition via algorithms (Ezrachi et Stucke (2017).

3.3. Antitrust Cases

It is algorithmic collusion that has been pointed out as a serious threat to the competition in the stage of the digital market. Algorithmic collusion though includes two concepts, a) algorithmic explicit collusion and b) algorithmic tacit collusion (Gautier et al, 2020). Cases of algorithmic explicit collusion are already documented. The "Amazon Poster Case" constitutes a representative example of algorithmic explicit collusion.

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Two sellers, GB Eye (GBE) Ltd and Trod Ltd in the online retail platform Amazon UK agreed not to undercut prices *for licensed sport and entertainment posters and frames*[7] (the core of the infringement according to the Competition and Markets Authority of the United Kingdom) when there was no cheaper third-party seller. The GBE Ltd is an international producer and seller of licensed sports and entertainment merchandise and one of the UK's two main producers and distributors. To understand the extent of its market power, it is important to state paragraph 3.6 of the relevant CMA case report:

> Producers license the content from entertainment companies such as Warner Bros, Disney, the BBC, Sony Pictures, Lucas Film, Marvel, 20th Century Fox, Nickelodeon, Cartoon Network, 15 as well as holders of imaging rights, for example, to The Beatles, Pink Floyd and One Direction. 16 Producers also similarly license rights from sports companies, such as Liverpool FC. Licenses tend to cover rights to produce and sell posters relating to a number of specific subjects rather than to an entire portfolio of subjects.

The Trod Ltd, on the other side, is a private company purchasing products from third parties and then re-selling them. In detail, it is an international retailer and wholesaler and its commercial activity is focused on the toys and licensed posters and frames trade. The relationship between the two Amazon UK sellers is that of the supplier (GBE) and the customer (Trod). The agreement was implemented in the Amazon Marketplace from March 2011 to July 2015 and was realized via automated pricing software, different for each party and programmed to fulfill the targets of the two sellers respectively. The "partners" had regular communications to check for the right implementation of the agreement and for technical issues concerning the pricing software. Consequently, the trade in the platform, by each side was made upon a carefully designed pricing algorithm. The CMA formally started direct investigations into both

[7] Competition and Market Authority, Case 50223/2016, Online Sales of Posters and Frames

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businesses' premises and respective software providers in September 2015. Financial penalties have been imposed only on Trod Ltd. Trod Ltd and Daniel William Aston, an owner and director of Trod Ltd (Krotoski M. et Ren F., 2019), has also been accused of conspiracy for price fixing on Amazon U.S. in the case U.S. v. D.W. Aston and Trod Ltd.

Another significant case involving pricing algorithms is the U.S. v. Topkins in 2015. It is about the participation of David Topkins, an individual, in a conspiracy with other persons and firms engaged in posters sales, i.e. in the production and sales, from September 2013 to January 2014. The goal was primarily to *fix, increase, maintain and stabilize prices* for posters sold in the Amazon Marketplace in the United States. For the purpose of implementing the agreement for price manipulation, Topkins and his co-conspirators agreed on the adoption of a pricing algorithm *with the goal of coordinating changes to their respective prices* (U.S. Department of Justice, 2015). That was the first antitrust e-commerce criminal prosecution in the United States. "We will not tolerate anticompetitive conduct, whether it occurs in a smoke-filled room or over the Internet using complex pricing algorithms," said in a statement Assistant Attorney General Bill Baer of the Justice Department's antitrust (Stempel, 2015).

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CHAPTER 4_Algorithmic Tacit Collusion

4.1. The Mechanisms behind

Pricing algorithms enforce a business' strength in three ways. First, implies cost reduction, as is already mentioned above. The limitation of human staff engagement in the pricing procedure induces lower staff expenses and confinement of behavioral biases. Nevertheless, configuring an effective pricing algorithm may be costly in the matter of time and expenses. For that reason, firms that cannot afford such an investment may recur to pay for a subscription to a pricing platform and thus use its software.

Using a pricing algorithm, the firm achieves fast price adjustments to market fluctuations such as cost changes and demand or supply shocks. These, almost immediate, price adjustments help companies price efficiently reducing, in that way, excess supply or demand cases and thus resulting in higher market efficiency. The stature of a seller on a platform is such that these prices clear markets worldwide. Furthermore, the platform's design may guide firms toward certain paths. For example, firms are shaping common incentives with the platform for increased output. This is even more possible to happen when platforms have an informational advantage over the businesses in the platform (some business models, such as Airbnb and Uber, almost exclusively rely on pricing algorithms). This advantage derives from its ability to accrue detailed information on the market characteristics mentioned above. In this way, the platform may guide firms' prices toward a competitive level (Oxera, 2017). It is as well significant how algorithmic pricing may reduce barriers to entry. No specific market knowledge is necessary. The algorithm is trained with appropriate data relevant to a specific market. This gives an advantage to firms acting in a limited range of products and potentially upgrades their portfolio with new entries.

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On the other side, threats such as Vertical Coordination may emerge more easily, taking into account transparency and platforms. Resale price maintenance (RPM) may be enforced as manufacturers monitor downstream prices. Competing platforms monitoring each other's prices may as well enforce Most-Favored Nation Clauses (MFN) and, as mentioned previously, a hub-and-spoke structure may emerge as platforms are delegated to set prices on behalf of the sellers (Oxera, 2017).

As long as the use of pricing algorithms takes increasingly more place at the industry level, transparency and risk of tacit collusion grow interdependently. This is due to sophisticated computer algorithms that process all available information and thus are able to analyze, monitor, and respond to competitors' actions. More precisely, it is for Reinforcement Learning algorithms or "Autonomous Agent" algorithms for which experimental or theoretical studies are conducted (see Chapter 2) to detect the underlying mechanisms that lead to pricing algorithms coordination with negative results for the competition. So far, only one algorithmic tacit collusion case is documented by Assad et al. (2020) on the German retail gasoline market proving that AI affects competition significantly. Generally, though, it is hard to detect the algorithm's conscious parallelism. Other alarming views are on the possibility of algorithms *establishing a hidden channel of communication, that may address problems of entering and sustaining collusion* (Ezrachi et Stucke, 2020). Consequently, the question to answer is if reinforcement learning pricing algorithms could choose conscious parallelism as an optimal strategy to achieve profit maximization.

According to the literature, tacit collusion may occur in an autonomous manner with limited or absent human intervention. More precisely, acting via trial and error, the algorithm interacts with its environment and implements various strategies in order to arrive at the desirable profitable outcome i.e. the optimal price. In that case algorithmic pricing is enforced by a model-free Reinforcement Learning method, where no market models, such as demand

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functions or competitor's cost functions, are needed to feed the pricing algorithm (Gautier et al, 2020). The mechanism relies on Artificial Intelligence and is able to act autonomously in unknown environments. The AI algorithm uses a set of potential actions i.e. today's price as input, for each possible observation e.g. past quantities and prices. Then, via the exploration-exploitation procedure, the algorithm deduces a profit-maximizing map of each observation and the corresponding chosen price (Assad et Al, 2021). The actions linked with a positive outcome, a reward, will have higher chances to be chosen in the future. The exploration-exploitation procedure results in a tradeoff that allows the algorithm to mimic the oligopolists' pricing tradeoffs derived from each price choice. More precisely, the algorithm experiments and learns the consequences of possible suboptimal prices (Calvano et al, 2019). The relevant literature studies the implementation of the Q-Learning algorithms, a new generation of Reinforcement Learning algorithms that incorporate autonomous experimentation with random actions, in their learning procedure.

The experimental analysis for algorithmic collusion has highlighted that there are strong arguments for it to happen. The Q-learning algorithm considered a possible AI pricing algorithm has several important "hyperparameters" that characterize its design. These parameters are the "rate of learning" and the "experimentation rate". The first represents the balance of what the algorithm has learned to date and the new observations. The second parameter is the probability the algorithm sets a possibly suboptimal price (in a period) in order to explore the reaction of the market (i.e. consumers and rivals). Likewise, necessary parameters are the discount factor that gives the firm's discounted profits, the memory of the algorithm (usually one or two past periods), and the discrete prices classified in a finite price grid. The list of important parameters that complement the virtual environment is filled with economic parameters such as the number of competing firms in the market and their own production cost, and consumers' demand, given by linear or logit demand functions (Assad et

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al, 2021). The complexity of the model and the results increases as the size of the aforementioned information sets is expanded. In the experimental study of Calvano et al (2020), the competing firms relying their pricing strategy on algorithms set prices significantly higher than those in the competitive benchmark as seen in the distribution below.

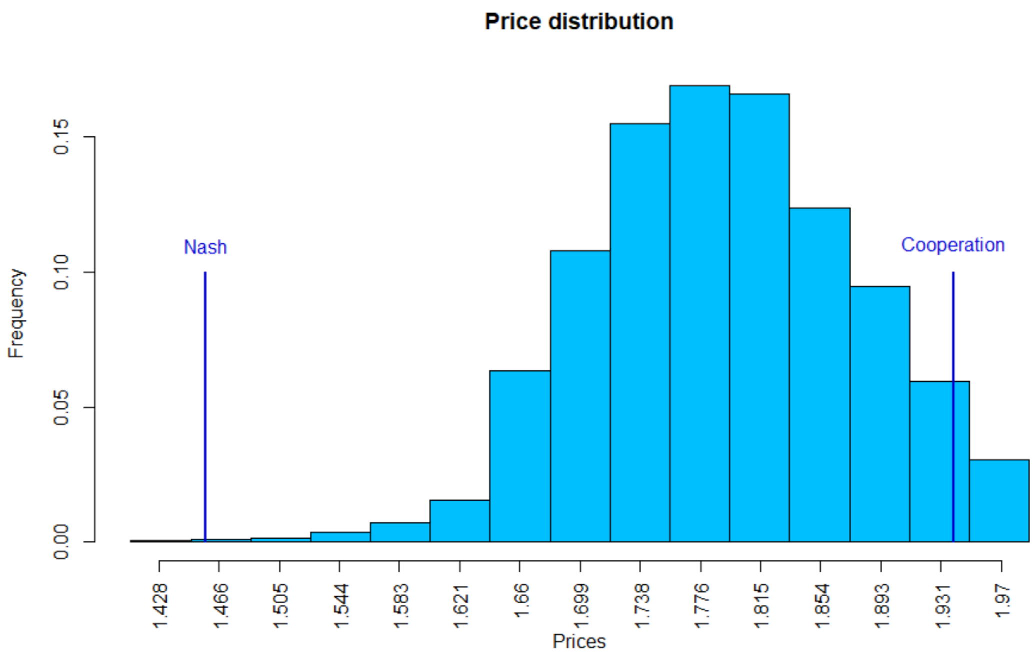

Figure 8 The distribution of prices charged by reinforcement-learning price algorithms in the virtual market created in Calvano et al. (2020). The price that would maximize the firms' joint profit is just above 1.93. The algorithms routinely learned to collude (Assad et al,2021).

The researchers find that this is a result of tacit collusion rather than a case of algorithms not being able to compete. That is demonstrated by experiments showing algorithms' reaction to rival's price cut. During the experiment, after each session, i.e. after the end of a learning phase, the algorithm is forced to set a lower price and thus induce a "shock" in the market for only one period and subsequently report that behavior to the next periods. The reaction of the

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competing firm is to follow the movement of the first firm and almost equally reduce its price too. The reaction of the first firm, then, is to follow the second's price. This is considered a temporary price war since it rapidly terminates returning gradually to the initial high prices before the "shock".

The reaction chain consisting of a) a reward (keeping prices high unless a price cut occurs), b) retaliatory pricing and c) forgiveness is the distinctive characteristic of collusion (Assad et al, 2021). Additionally, Calvano et al (2020) prove the robustness of the algorithmic tacit collusion experimental findings and conclude that this competition distortion is feasible even a) with increased number of firms participating in the market, b) when there are different cost functions or product quality, c) with different degrees of product differentiation, d) with stochastic demand, although coordinating in reduced high prices, e) with variable market structure (unpredictable firms' entries and exits), f) with imperfect information and monitoring, and g) with changes in the *"hyperparameters"*.

In addition, other important inquiries emerge. In the case where a "new algorithm" enters the market, which strategy will it follow? Will it adapt to the already existing algorithms' setting of collusion ending with a possibly reduced new equilibrium (because of the adding firm) or exploit the high prices to its favor? Are the collusive strategies the algorithms learned specific to the events they faced in their learning history? According to Assad et al (2021), the latter can be checked by taking differently trained algorithms and letting them compete in a new virtual market environment. It is assumed that the algorithms will start engaging in a price war but after events of punishments of deviations then accord in a new collusive equilibrium.

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Coordination of firms without communication emerges in repeated games with infinite time horizons[8]. This is cooperation arising from a self-interested calculation of the benefits and losses that may accrue from "polite" behavior. Though, without previous communication, cooperation is possible if we rely on a convention or learned behavior or a focal point, or something equally vague (Kreps D., 1990). Based on grim-trigger strategies of punishments and rewards (stick-and-carrot strategy), tacit collusion emerges as a subgame perfect Nash equilibrium in an infinitely repeated oligopoly game. According to the literature, tacit collusion is feasible to sustain provided some key conditions such as symmetric firms, market transparency, [as long] as firms have a large enough discount factor (Belleflamme et Peitz, 2010), multi-market competition and the likelihood of entry (Gautier et al, 2020).

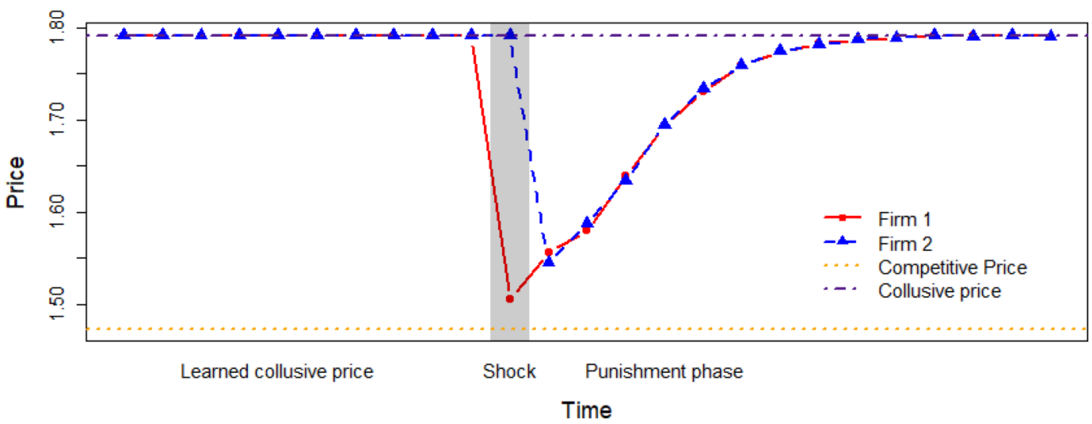

Figure 9 **After the two algorithms have learned their way to collusive prices, an attempt to "cheat" so as to gain market share is simulated by exogenously forcing one (Assad et al,2021).**

of the two algorithms to cut its price. From the "shock" period onwards, the algorithm regains control of the pricing. The deviation is punished by the other algorithm, so firms enter into a

[8] *Cooperation is not possible in the standard version of the prisoner's dilemma repeated a finite number of times* (Laraki et al, 2019).

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price war that lasts for several periods and then gradually ends as the algorithms return to pricing at a collusive level. [Source: Calvano et al. (2020). Copyright American Economic Association; reproduced with permission of the American Economic Review.]

4.2. Likelihood of Tacit Collusion in Certain Markets

Tacit Collusion is more likely to appear in certain markets, sharing three important characteristics, according to Ezrachi et Stucke (2020):

i. In concentrated markets with homogeneous goods.

In that type of market, the algorithm can sufficiently monitor the competitor's pricing stream, key terms of sales, and deviations from the collusive equilibrium. Market transparency is key to this development and is gained not only by the increasing data availability but also by the algorithms' prediction ability and thus reduction of market uncertainty[9].

ii. In markets with a credible deterrent mechanism.

Once deviation by a firm occurs, the software can rapidly detect and calculate numerous moves and counter-moves to punish that, making it unprofitable to deviate. The speed of retaliation signifies the instantaneous signaling of tacit collusion. As pointed out, the greater the improbability that the first-mover will benefit from its discounting, the greater the likelihood of tacit collusion. Moreover, market stability, important for tacit collusion, *is enhanced by the fact that computer algorithms are unlikely to exhibit human biases*[10].

[9] From another point of view though, data is a scarce resource that exhibits decreasing returns to scale in a technical sense (Varian, 2018).

[10] Nevertheless, technical issues arise regarding the optimal implementation of pricing algorithms. For example, an overlooked aspect of the proposed pricing models concerns their scalability which can lead to high memory

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iii. Outsiders (customers and other competitors) of the coordination are not able to jeopardize the results of the tacit collusion.

Explicitly, in such concentrated markets, the buyers a) cannot exert buyer power, b) there are frequent, regular, and relatively small sales transactions and c) there are high entry barriers.

and processing time requirements, unreasonable and beyond the reach of most firms according to Gautier et al (2020). For an environment described by m states, consisting of n agents, and where each agent can perform A possible actions, the total space requirement is nmA^n, which is exponential to the number of agents. Another technical issue arises when multiple agents act in the environment. The environment is made non-stationary and the mechanisms proposed to deal with it are specific to agents that rely on deep reinforcement learning (e.g. deep Q-learning) and not the classic Q-Learning model upon which most researches are based. Additionally, the issue of temporality, i.e. the time needed for the algorithm to explore the environment and learn is significantly high. Gautier et al (2020).

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CHAPTER 5_Literature Review

5.1. AIA pricing and Collusion evidence.

Big data processing and analysis along with the advancement of digitization and artificial intelligence led to new applications of algorithmic pricing (Wieting and Sapi, 2021). Especially ML use in pricing has altered the view of the market and has given rise to new opportunities to adjust prices based on consumers' characteristics (Varian, 2019). AI may also facilitate a firm's entrance into a market by harnessing observable prices and revealing investment opportunities or even practicing "hit and run" entry if prices fall significantly, whereas it improves its internal processing. It may, as well, help incumbents or potential entrants to understand more accurately consumer demand e.g. abundant online product reviews can be processed by AI programs and suggest a successful new product or a variant of it (Johnson and Sokol, 2020).

Additionally, improved innovation in products by the use of AI and, furthermore, ML algorithms used to support consumers' choices by providing product comparison and price fluctuation analyses, definitely benefit consumers. Nevertheless, certain concerns emerged, in recent years, regarding algorithmic pricing and along with the increasing implementation of it in several industries. More precisely, the concerns are about the possibility of pricing algorithms interaction to elicit tacit collusion in the digital marketplace and keep prices high. A collection of the relevant literature attempts to clarify the problem of algorithmic tacit collusion and state the prerequisites to happen and sustain.

If firms engage in an explicit industry talk about prices and there is evidence for it, this *is often the smoking gun in antitrust procedures and it usually presents a per se violation of competition law* (Fonseca and Normann, 2012). In repeated games, there are many equilibria, and according to the folk theorem, any outcome can be sustained as an equilibrium in a

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repeated game. In that framework, interactions among oligopolists are viewed as a repeated game and collusive outcomes attract the interest of economists.

Waltman and Kayman (2008) show that firms using Q-learning algorithms learn to collude. The researchers model how firms learn using Q-learning algorithms in a repeated Cournot oligopoly game. The study considers two sets of agents: a) both agents with memory and b) both agents with no memory. No memory agents cannot reclaim the results of current action in future payoffs. In the repeated Cournot model, firms may maximize their individual long-term profits contrary to the static one. In that case, if they have a memory of past actions, it is possible to sustain collusion. Computer simulations, though, highlight that two competing firms using Q-learning without memory can still develop a collusive behavior. When experimentation of the algorithm is allowed in the model, then firms may differentiate their position from the collusive state to the Nash state and the contrary. Though, results show that firms will spend most of their time in a collusive state.

Chen et al (2016) focus on the Amazon Marketplace and especially on Amazon's Buy Box, a special "section" in the platform featuring selected sellers gaining customers' "trust" to select specific products by specific sellers. That choice was made due to Amazon's magnitude and e-commerce share on both sides of the Atlantic. In addition, Amazon is a true market with third-party sellers acting along with Amazon itself. A third important characteristic is that Amazon's platform APIs are designed to facilitate algorithmic pricing. Researchers, first, develop a methodology in order to collect data and detect which sellers are likely using algorithmic pricing. Then, examine the dynamic pricing strategies used by sellers and compare the characteristics of sellers that use AI pricing and those that do not. Findings show that Buy Box exacerbates the disparity between algorithmic and non-algorithmic sellers as it creates a largely winner-take-all marketplace but there is no clear view of the impact of dynamic pricing on customers.

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In their work, Zhou et al (2018) propose a specific algorithm, designed to enforce its human rival to optimize its own payoff. Both human and the algorithm compete in a Cournot duopoly market. Under this concept, algorithmic collusion is an inevitable outcome of a rational spirit. The experiment shows a continuous increase in the degree of collusion and at the same time a decrease in social welfare. Although the study does not experiment on reinforcement learning algorithms, it still considers algorithmic collusion a creditable threat.

According to Calvano et al (2019), algorithmic pricing shall initiate a new era of competition policy monitoring, approaching the subject under the relevant law, economics, and computer science literature. In the large online marketplace, significant sellers like Amazon in the US have adopted algorithmic pricing and serve an equally significant number of customers. It seems that the demand for ML pricing will keep increasing. The first concern is that algorithmic pricing (AP) will enforce price discrimination further as prices suggested the software will be conditioned on not only basic and innocent information like the timing of purchase but also the history of past purchases which could lead to the use of exclusivity or market share discounts, both of which may have anti-competitive effects.

AP may also facilitate collusion even if they are innocently designed, due to the second-generation algorithms it uses, ie. the learning algorithms. Learning algorithms, experiment to learn the consequences of possibly suboptimal prices in the sense of assessing every possible position, and by that they learn how to play optimally. These model-free algorithms, which do not need to specify a demand function and hypothesize about the rival's behavior, excel in complex and quickly changing environments relative to the first-generation "adaptive algorithms". Focusing on the Q-learning algorithms, as they form the basis for more sophisticated algorithms that among others may learn how their rivals learn, the researchers study their properties and check for the three important challenges an algorithm faces ie. stability, adaptation, and scalability.

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Q-learning algorithms seem to satisfy more or less each of them. Adding to that neural networks and deep learning methods, give algorithms the ability to deal with high-dimensional state spaces and thus generalize from experience i.e. estimate Q-values for not visited "states". Algorithms' collusive strategies may also be realized via the special communication they build by developing their own common language thus they are more effective to collude than managers are. Since AP sets new problems for competition policy, Calvano et al. (2019) discuss four possible approaches, the ex-ante and the ex-post regulation of AP introduction, the total prohibition of AP, and the "no reason" to intervene as an optimistic view. The first two are discussable, although ex-ante regulation represents a form of public intervention. The last two seem to be baseless since studies show that algorithmic collusion is a real fact. On the other hand, we cannot prohibit AP due to the big efficiency gains by allowing more efficient pricing. Definite policy recommendations are avoided due to unknown AP characteristics.

Miklós-Thal and Tucker (2019) present a theoretical model under certain limitations, considering an infinitely repeated game, where firms update their beliefs about the demand, given a specific signal (ρ) they observe, according to Bayes' rule. They check for collusive behavior when firms use pricing algorithms and approach it by the aspect of the improvement of demand predictability they achieve. The concluding results show that improved prediction ability may benefit consumers' welfare. This is due to the fact that more accurate demand prediction increases firms' tendency to undercut the price when there is a high predicted demand. This, also, limits a cartel's ability to set high prices during these periods.

The first empirical paper dealing with algorithmic pricing and competition implications is that of Assad et al (2020) which investigates the mass adoption of AI-pricing software in the German retail Gas market in 2017. Assad et al (2020) access a high frequency, database of prices and characteristics for every retail gas station in the country and identify which stations have adopted the pricing software when they observe structural breaks in at least two out of

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three measures of pricing behavior i.e. (i) the number of price changes, (ii) the average size of price changes, and (iii) the rival response time. The study finds that only in the case of the market where two stations, both adopt the software, a mean margin increase of nearly 30% is revealed. In addition, the timing of effects proves that algorithms learn how not to compete, facilitating tacit collusion in the specific German retail gas market. This is considered a reason for concern when thinking of the massive adoption of AI pricing software in markets.

In 2020, Calvano et al published the paper "Artificial Intelligence, Algorithmic Pricing, and Collusion" in the American Economic Review. The objective of the study was to demonstrate if the use of algorithmic pricing by firms, based on recent software incorporating Artificial Intelligence, could lead to collusion. Researchers test the autonomous decision-making process of reinforcement learning algorithms in order to conclude with robust results. They take a fully controlled experimental approach, using specifically the Q-learning algorithms due to their popular use among computer scientists in general and also to their simplicity and the fact that they share the same architecture with more sophisticated programs achieving superhuman performances.

As a baseline model, the researchers used a symmetric duopoly with deterministic demand, acting in a repeated Bertrand oligopoly environment. The findings of the study show that Q-learning pricing algorithms indeed learn collusive strategies and the collusion state is imposed by punishments occurring after firms decide to deviate. The algorithms coordinate on prices that are significantly higher than the static Bertrand equilibrium and below the monopoly prices, which imply higher profits. In terms of competition policy, researchers suggest that the study's results should probably ring an alarm bell.

Current antitrust laws may not even characterize algorithmic collusion as illegal (Assad et al, 2021) and thus produce many false negatives. In parallel, algorithmic pricing gives antitrust

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agencies the potential to test firms' (under investigation) pricing algorithms in environments that replicate the respective industry which is not possible with human agents. This may reduce false positive decisions of aggressive antitrust enforcement. Calvano et al's findings are also checked for robustness under different economic parameters like stochastic demand, firms' asymmetry, different degrees of product differentiation, variable market structure, and under changes in hyper-parameters of the algorithm, namely the rate of learning and the experimentation rate. Even after incorporating different elements than the base model, algorithms stubbornly present collusive outcomes. Though, as a final note, researchers highlight the need for a better understanding of the learning process dynamics.

Johnson et al (2020) experiment with the design of a digital market platform. They provide evidence on the feasibility of designing platforms that can promote competition, increase consumer surplus and at the same time increase its own profits. The setting considers multiple firms with differentiated products under the standard logit model. The researchers check for two platform design policies/rules, a) the PDP (price-directed prominence) which orients demand towards sellers that charge lower prices in a certain category, and b) the Dynamic PDP. Both policies rank and display products and consequently provide the consumer with a subset of available products. PDP does not perform well when sellers collude but Dynamic PDP responds better to that challenge by steering demand to the firm not only during the period where this firm set low prices but also in later periods subject to some restrictions. This inevitably makes it difficult to impose punishment to a firm that has cut prices and thus cartel stability reduces.

The findings show that when a platform acts out of a PDP framework, then the algorithms set prices that exceed the predicted Bertrand- Nash prices. In general, when applying Dynamic PDP policy, the raise in consumer surplus can exceed 35% and at the same time the platform raises its profits depending also on its revenue model. The Q-learning algorithm is once more

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used in this study. The findings show that allowing for "smarter" AIA in a Dynamic PDP framework, we achieve a remarkable increase in consumer's surplus.

Calvano et al (2021) extend their research on algorithmic collusion and build their experiments in the special environment of imperfect monitoring. They use the classic model of repeated interaction under imperfect monitoring in Cournot oligopoly competition by Green and Porter (1984). In that model, firms set quantities and are able to observe price levels but cannot perfectly deduce rivals' output after observing past prices due to stochastic demand. In that study, Calvano et al presume that all firms use algorithms of the Q-learning type and that the firm's algorithm under question repeatedly plays against an identical opponent.

The results show that when Q-learning pricing algorithms are given enough time to learn, they can still collude, even under the stochastic environment of imperfect monitoring that may otherwise hinder collusion to some extent. Notwithstanding collusion is decreased and uncertainty reduces profit gains relative to perfect monitoring conditions at Calvano et al (2020), supra-competitive profits are still realized. It is remarkable that algorithms learn strategies, that sustain the collusive outcome, similar to those considered by Green and Porter (1984), and despite the fact that algorithms appear a short-lived memory by design relative to rational agents, they manage to outmaneuver this obstacle by resorting to the ingenious "behavior" of learning to use the intensity of the punishment as a substitute of a longer memory.

Nevertheless, when researchers allow firms to condition their period-t output for two more periods, they observe that a 3-period memory reduces profit relative to the first two. It is assumed that since memory increases, the Q-matrix of values becomes bigger, and that hinders learning. Calvano and al's experiment cannot provide conclusive evidence of algorithmic collusion under imperfect monitoring in practice but highlights the fact that it has a strong

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possibility to happen. According to the paper, future studies shall focus on diverse and asymmetric algorithms, the speed of learning, the possibility of firm-specific shocks, and other factors that may hinder algorithmic collusion.

In their paper, Asker et al. (2021) focus on reinforcement learning, ie on Artificial Intelligence Algorithmic pricing. They set a simple Bertrand duopoly model with homogeneous goods and use a variant of Q-learning algorithm as introduced by Watkins (1989). The design of the algorithm has a material impact on the observed price outcomes and is dependent on the complexity of the firms' economic environment and their will to invest in the AI program supporting the algorithm.

The researchers unfold two different learning protocols, the synchronous and the asynchronous which focus on and exploit different information from their environment. Then they test for two different cases, a) an algorithm designed to maximize future discounted profits and b) an algorithm maximizing current returns. We observe different rest points in the algorithms that link to different equilibrium notions. In a setting where firms do not care about future profits, ie $\beta=0$, the asynchronous updating leads to high prices whereas synchronous to competitive. Quite the opposite happens when $\beta>0$. The findings show that implementing AIA with asynchronous learning protocol proves to be a Nash equilibrium for both firms, since no matter what learning protocol the rival firm chooses, each firm is better off with the asynchronous algorithm. In addition, in both learning protocols, the more firms enter the market, the more reduced is any supra-competitive pricing.

Veljanovski (2022) cites the latest developments in the field of algorithmic pricing. He highly criticizes concerns regarding algorithmic collusion since there is no evidence or any antitrust case that highlights the threat of reinforced-learning pricing algorithms. By the sides of economic and computer science literature, prospects of algorithmic collusion have not been

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much supported. There are only a few experimental pieces of evidence of algorithmic collusion and only one empirical study by Assad et al (2020) which highlights the effects of pricing algorithms by German bricks-and-mortar retail petrol stations.

Veljanovski states that what has being done so far in the field, does not actually constitute valid evidence of algorithmic tacit collusion. These studies fail, as well, first to define clear price effects of algorithmic collusion since prices are between the collusive and competitive pricing, second to check for cases where different firms use different pricing algorithms (so far studies suppose firms using the same pricing algorithm), third do not refer to contrary experimental evidence as in a case incorporating Miklós-Thal and Tucker (2019) do in their game-theoretic model. The fourth failure of these studies is that are inconsistent with discriminatory and personalized pricing which are opposite to successful collusion. The overall conclusion is that if machine collusion is about to threat competition at some time point, this could be only in a few markets and especially in markets that are already susceptible to collusion.

Brero et al (2022) model the interaction between the sellers and a digital platform. More specifically, they demonstrate that reinforcement learning can be used by platforms to learn "buy box" rules (see Amazon's "buy box" case) that prevent collusion by reinforcement learning sellers and at the same time do not reduce consumer choice. The platform in fact sets rules of a "buy box" that decides which sellers are displayed to "buys". The researchers use a variation of the Stackelberg Markov Decision Process (MDP) methodology. The competition between sellers for consumer demand is modeled through the standard logit model for consumer choice. The paper proves that effective interventions at the platform can be learned using machine learning methodologies and that the introduction of threshold policies optimizes consumer surplus.

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Peiseler et al (2022) propose a theoretical model that captures only one key aspect of the use of pricing algorithms and this is the improvement of data analysis for better price discrimination. Horizontally differentiated firms price discriminate based on private, imperfect information. The paper examines the firm's behavior and especially the collusion trend under this setting. The findings show that a better prediction of customer preferences has a U-shaped effect on firms' ability to sustain collusion where collusion is easier to sustain under price discrimination and low levels of predictive capabilities.

The paper of Sanchez-Cartas, J. M., & Katsamakas, E. (2022) is a real contribution to the latest developments in algorithmic pricing research, considering two sophisticated AI algorithms, Q-learning and Particle Swarm Optimization (PSO) which is a stochastic optimization technique. Both algorithms compete in prices in three different markets (Linear demand models, Logit and Hotelling). They check for firms competing with each other using the same algorithm, using different algorithms, and also competing with a traditional best-response firm. Findings show that the Q-learning algorithm sets supracompetitive prices in all three markets whereas PSO tends to set competitive prices in several markets. Nevertheless, the degree supracompetitiveness changes between markets due to market characteristics.

To the extent that different firms compete with different pricing algorithms, Q-learning is the one that sets lower prices. This is considered to be a result of the interaction between the algorithms since both explore and exploit but by using different rules and timings. The study reveals that the algorithmic design is essential because the appearance of supracompetitive prices may be a consequence of an ill-designed algorithm. This implies that competition authorities should devote more resources to capture the behavior of the algorithm possibly in a case-by-case approach. Another result of the study is that the algorithm with the more extensive exploration phase, will have an advantage over the competitor similar to Stackelberg leader, if interacts indefinitely. It is considered necessary for policymakers to concern on AI pricing but this should be conditioned on the specific algorithmic design and the market structure. Managers, as well, should be careful when using pricing algorithms because there is neither one-size-fits-all solution nor will it always be robust even if profitable. This means that human supervision and intervention is a requirement.

Asker et al (2022) study how AI Algorithm's learning protocols lead to competitive or supracompetitive price outcomes. The algorithms act in a Bertrand pricing game but do not value future profits. They value profits in the present state only. With this setting, researchers rule out "collusive"-style equilibria where the action in the current period is formed by estimating future returns. A reinforcement learning algorithm consists of three elements: (i) a set of values interpreting the estimation of profit conditional on setting each feasible price, (ii) a method of price selection, and (iii) a selected updating rule which uses the firm's observations of a period in order to update the perception of expected profits and to generate next period's perception.

The way algorithms update their perception of expected profit shapes the way the algorithm learns the returns of an action. The study considers three updating rules: asynchronous updating, synchronous updating using downward demand and perfect synchronous updating where the algorithm calculates exactly counterfactual profits. The findings show that by ruling out "collusive"-type strategies we explore new paths of algorithmic influence on pricing. More precisely, AIA' s interaction in the market, under this setting, leads to a price increase highlighting that the design of the AIA's core learning protocol can be a key determinant of the extent to which pricing outcomes are competitive.

A different approach contrary to the application of the Q-Learning method is tested by Wang Yangen (2022). Wang studies decision-making algorithms on equilibrium outcomes in simultaneous Bertrand and Cournot duopoly and oligopoly environments. Contrary to value-based reinforcement learning model of Q-learning, this study uses the Natural Policy Gradient method, a type of policy-based reinforcement learning algorithm where, as in the “normal gradient”, agents learn parametrized policies $\pi\theta$ by optimizing the expected returns with respect to θ, but performing better and in a faster convergence rate.

In the normal gradient ($\nabla\theta\eta(\theta)$), agent's decision is denoted by $\pi\theta$ ($\alpha t|st$) representing probability distributions of actions over states and they update their policy parameters according to the long-term expected rewards [$\eta(\theta) = E\tau \sim \pi\theta (\tau) [r (\tau)] = E\ \tau \sim \pi\theta (\tau) [\Sigma t\ r (\alpha t, st)]$, where τ is the trajectory under policy $\pi\theta$].

Thus, better actions will be selected with a higher probability. In the Natural Policy Gradient method, we are not using the normal gradient but the Fischer information matrix ($F(\theta) = E\tau{\sim}\pi\theta(\tau)\ [\ \nabla\theta \log \pi\theta\ (\alpha|s)\ \nabla\theta \log \pi\theta\ (\alpha|s)T]$) that measures the curvature. Thus, the improvement of policy parameter in each step is given by

$$\boxed{\theta \leftarrow \theta + \alpha\nabla_{\theta}\ \eta{\sim}(\theta) = \theta + \alpha F(\theta)^{-}}$$

The paper concludes that decision-making algorithms based on the Natural Policy Gradient method consistently converge to Nash equilibria both in simultaneous Bertrand and Cournot duopoly and oligopoly environments. This is opposite to the collusive behaviors of Q-learning algorithms, depicting that the risk of algorithmic collusion depends on various factors, including the choice of machine learning algorithm. The author states that these exceptions in algorithmic collusion may provide useful insights into developing regulatory policies for decision-making algorithms. Furthermore, this method accords better with real-world situations since it studies continuous action and state space, contrary to the Q-learning and Deep Q-Network methods. More precisely, the Q-learning algorithm is characterized as a slow learning-algorithm, has no theoretical convergence guarantees and applies only to discrete space, elements that hamper its application in real-world scenarios. Nevertheless, a drawback of the

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tested method is the large variance of the gradient estimator which similarly slows down the learning process.

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CHAPTER 6_Artificial Intelligence International Context

6.1. The Ethics of AI

Ethical issues arising from the diffusion of Artificial Intelligence concern people, politicians, and scientists. A plethora of articles and scientific papers anguish over the effects of AI on individual privacy and other areas of human life. The origins of these worries derive from the complexity of the machine-learning algorithms incorporating deep neural networks and supported by the latest technological developments. It is a new field, acquiring a multi-dimensional approach from many different scientific disciplines.

Regarding the field of pricing algorithms, apart from concerns relevant to the possible algorithmic tacit collusion which is analyzed in the previous section, there are high concerns when the firms apply price discrimination to consumers. Traditional forms of price discrimination such as those based on socio-demographical characteristics, e.g. the operational system/device via which the consumer communicates/connects with the platform or the region it comes from, are commonly used and so far known to the experts. These technics are straightforwardly implemented with the support of rule-based methods, e.g. (IF-THEN-ELSE), or of traditional clustering algorithms. Finer-grained price discrimination is possible to happen based on more sophisticated econometric methods coupled with consumers' behavioral data. This enables a more accurate individualistic approach when pricing a consumer. Consequently, that entails growing firms' profits (Gautier et al, 2020). If considering then that someone controlling a platform is allowed to compete with people who depend on that platform, it is obvious that it will inevitably lead to competition distortions (Rosenbush, 2022).

An incident of "traditional" price discrimination was featured in the New York Times and is related to the U.S. brand "Target", a chain store that used Artificial Intelligence and data analytics for forecasting women's pregnancies and sent them advertisements in the form of

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website ads for baby products (Duhigg, 2012), exerting a "silent" manipulation of consumers' behavior. Another incident has been Uber customers complaining about paying more when their smartphones' batteries were low (Petropoulos, 2022). Websites' cookies constitute a common resource of information whereas others are credit cards, e-mails, and loyalty card numbers (Kuhn, 2023).

Data persistence, the lifetime of data value, i.e. for how long data acquired today will continue to be useful, is another issue that conflicts with privacy. According to Tucker (2018),

> data that was created at t = 0 may have seemed innocuous at the time, and in isolation may still be innocuous at t = t + 1, but increased computing power may be able to derive much more invasive conclusions from aggregations of otherwise innocuous data at t + 1 relative to t. Second, there is a whole variety of data generated on individuals that individuals do not necessarily consciously choose to create. This not only includes an incidental collection of the data such as being photographed by another party, but also data generated by the increased passive surveillance of public spaces, and the use of cellphone technology without full appreciation of how much data about an individual and location it discloses to third parties, including the government.

Additionally, algorithms may create spillovers between individuals and other economic agents. For example, a person's decision to keep some information secret in the virtual globe, may signalize and predict other aspects of the individual's behavior. Furthermore, when a firm possesses superior knowledge of its customers, i.e. has an informational advantage, then that clientele may not be of other firms' interest and thus encouraging these to increase their prices, damaging consumers' welfare (Acemoglu, 2021).

Democracy may be damaged by the automation of the production process making labour a dispensable element of the latter since, according to Acemoglu (2021), to an extent, democratic politics depend on different labour and capital, having countervailing powers against each

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other. Inequality as well increases due to faster automation and the introduction of new tasks (Acemoglu, Restrepo, 2018). Moreover, the autonomous behavior of an acting algorithm enforced by Artificial Intelligence and consequently, its decision-making[11] capacity are subject to the bias of the trained algorithm. Considering the fact that this is due to unintended imperfect training, it is an additional reason for a critic because in that way the algorithm can act in a discriminatory way, and that is an established fact as seen in Tucker (2018). If we consider that AI is a general-purpose technology, that fact may have widespread consequences (Agrawal et al, 2018). From another point of view, AI (in general) is considered more unpredictable, more diffuse, and less visible because of its lower threshold for use (Thornhill,2022).

Putting together the aforementioned components, we can shape a clearer view of the extent of AI's ambiguous results. A representative example of such ambiguity is presented by Lambrecht and Tucker (2018). In that empirical study, Lambrecht and Tucker explore how ads perform when algorithms their setting is delegated to algorithms. Previous studies have shown that, based on historical discrimination issues against groups, undesirable ads are more likely to appear than desirable ones. Though, the way algorithms act like that is a difficult subject for which empirical tests have proven its origins. More precisely, in that study, the researchers focus on ads promoting job opportunities and training in STEM (Science, Technology, Engineering, Math), motivated by the shortage of graduates in STEM fields, especially among women, as policymakers regularly complain about. This comes in contradiction with the findings of Williams and Ceci (2015) showing that in an academic context, women have more possibilities to be hired in STEM jobs than men, conditional on applying. Researchers say that this is an auspicious time to be a talented woman launching a STEM tenure-track academic career, contrary to findings from earlier investigations and they support that women's

[11] *Algorithms that make decisions can be considered blameworthy agents* (Mittelstadt et al, 2016)

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underrepresentation in STEM careers is an outcome coming from the supply side i.e. from women's decision not to apply rather from the demand side demonstrating antifemale behaviors. Lambrecht and Tucker (2018) though prove that the ads, although gender-neutral on their targeting group, were shown to over 20% more men than women although if women ever show the relevant ad were more likely to "click" on it. This bias occurred in an attempt of the algorithm to minimize costs. Other advertisers value more the opportunity to show ads in female eyes than men. Therefore, having on one side the advertisers that have a high willingness to pay for women's ads, and on the other hand, a gender-neutral ad, is where the collision happens. This means that since the algorithm is designed to minimize cost, the second ad will appear to fewer women (Tucker, 2017).

The unknown implications of deep learning and neural network technologies further concern experts on the effects of the so-called "black box" part of the algorithm. Consequently, the explainability of the algorithm and the transparency (starting from the design process) constitute inquiries that need to be addressed. A possible answer to that call could be the publishment of all algorithms after a certain period, following the patents' method (Seele et al, 2021). In any case, algorithmic impact assessments and algorithmic auditing are considered to be the best practices in artificial intelligence deployment (Coglianese, 2022).

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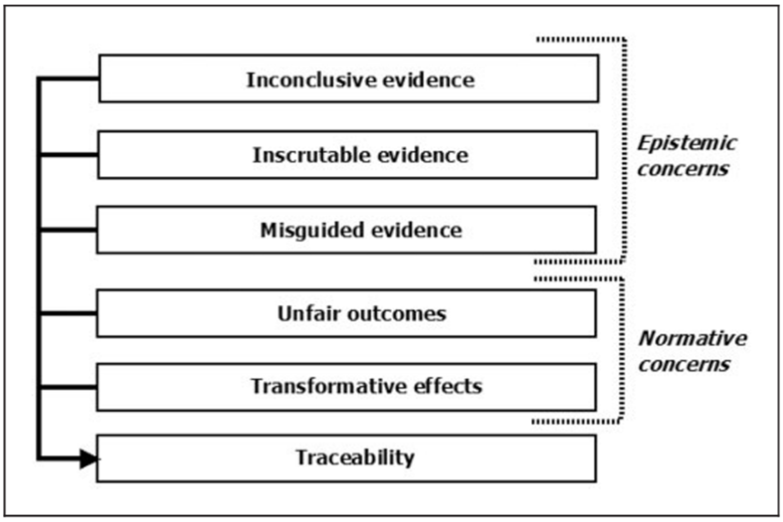

Figure 10 **Six types of ethical concerns raised by algorithms (Mittelstadt et al. 2016).**

6.2. Institutional Approaches

6.2.1. Europe

i. European Union and AI

The European Union has, so far, paved a remarkable path for Artificial Intelligence regulation and taken a number of initiatives. Its strategy for AI relies on a human-centric base and is a part of the EU's strategy for Europe's Digital Decade. The Digital Decade is a wide framework based on the guidelines of the Digital Compass, a compass of digital-related goals for the next decade. This policy framework incorporates any aspect of innovation and technology. Its goal is to ensure that technological development complies with certain principles and works for people in terms of accessibility, security, and availability whereas overall complies with democratic values and rules. All of its goals are measurable and comprise developments in the fields of digital businesses, digital public services, digital skills and connectivity.

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The European Union has settled the "European AI Strategy" aiming to make Europe a trustworthy and human-centric AI world-class hub. In its Communication (2018) to the European Parliament, the European Council and the Committee of the Regions themed "Artificial Intelligence for Europe", the European Commission states clearly the importance of AI in people's lives and highlights the advantages of this technology in the energy sector, financial markets, transport, manufacturing, medicine and other areas. It stresses the challenges, such kind of innovations bring, and supports the capitalization of a European AI approach taking advantage of world-class researchers by building an ecosystem of excellence in AI, of common rules on a Digital Single Market, the plethora of industrial, public sector (e.g. related to public utilities, environment) and research and health data. On the other hand, it is considered crucial to ensure an appropriate ethical and legal framework while at the same time being prepared for any socio-economic changes that AI will definitely bring to education, training, and to labor markets, demanding the adaptation of social protection systems.

In April 2021, the European Commission published an AI "package" to disseminate the importance of AI for Europe. The first was a Communication on fostering a European approach to AI both in terms of development and human rights protection presenting a proposal for a regulatory framework on AI and a review of the Coordinated Plan on AI with the EU Member-States. The Coordination Plan is a necessary complement of the launched AI package, dedicated to accelerating investments of over 1 billion € per year exclusively in AI technologies for resilient economic and social recovery, timely and fully implementing the relevant AI programs and strategies and aligning EU-wide AI policy in order to address worldwide challenges and compete globally.

A number of fundamental rights in the EU Charter of Fundamental Rights are seen to be affected by the fast evolution of AI systems. According to the proposal, these are the rights affected: the right to human dignity (Article 1), respect for private life and protection of

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personal data, nondiscrimination and equality between women and men, the rights to freedom of expression and freedom of assembly, the right to an effective remedy and to a fair trial, the rights of defense and the presumption of innocence, the general principle of good administration. Though, in certain cases, the proposal will positively affect the rights of some special groups, e.g. the workers' rights to fair and just working conditions, a high level of consumer protection (Article 28), the rights of the child and the integration of persons with disabilities the right to a high level of environmental protection and the improvement of the quality of the environment, including in relation to the health and safety of people.

Since AI has risen to an issue of strategic importance in terms of security, geopolitics and commercial stakes, the EU launched a risk-based regulatory approach. The proposal for regulation includes a set of harmonized rules that are applied a) to the AI design before being placed on the market, b) to the usage framework of high-risk AI systems and introduces ex-post controls and restrictions on certain uses of biometric identification systems. The logic under the proposal is to intervene only where it is strictly needed, minimizing the burden for economic operators and with the presence of light governance. On the other side, the proposal sets some restrictions regarding the rights to the freedom to conduct business (Article 16) and the freedom of art and science in order to ensure compliance with overriding reasons of public interest e.g. health, safety, consumer protection.

The proposal for a regulation, named also as AI Act, differentiates AI systems into four categories, according to the intensity of a possible risk stemming from their usage. Thus, there may be cases of AI systems with a) an unacceptable risk, b) a high risk, c) a low risk and d) a minimal risk. The classification of AI systems as high-risk depends on a combination of characteristics, namely their planned purpose and the severity and probability of possible harm. More precisely, it refers to the potential manipulation of humans via subliminal manners, "skipping" the conscious or maneuvering vulnerable groups of people e.g. children.

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Manipulative practices affecting adults could be covered by the existing legislation concerning consumer protection, digital services and data protection contextually. Examples of high-risk systems are those related to employee recruitment, creditworthiness evaluation and judicial decision-making. The listing of new upcoming AI systems as high-risk is also considered possible under certain predefined use areas.

Although four policy options, relevant to different degrees of regulatory intervention, were evaluated against societal and economic impacts, with a particular focus on fundamental rights, only one was selected. This is the regulatory framework for high-risk AI systems only, with the possibility for all providers of non-high-risk AI systems to follow a code of conduct. This option keeps compliance costs to a minimum. Especially regarding SMEs, this framework comprises supporting tools regarding their compliance and cost reduction and the creation of regulatory sandboxes, whereas considers the SMEs' interests when setting fees related to conformity assessment.

In order to mitigate the risks emerging from the use of AI, there have been settled several requirements for high-risk AI systems to accomplish. The requirements consist of high-quality of data, documentation and traceability, provision of information, transparency, and human oversight. Regarding transparency, this obligation concerns AI systems that a) interact with humans, b) are used to detect emotions or determine association with (social) categories based on biometric data or c) generate or manipulate content ("deep fakes"). The increased transparency obligations will proportionately only affect the right to protection of intellectual property. AI systems, as well, should perform with consistency throughout their lifecycle reaching an appropriate level of cybersecurity, robustness and accuracy. Robustness refers to resilience against system malfunctions and malicious actions that may jeopardize security and thus result in undesirable behavior with a negative impact on fundamental rights.

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Cybersecurity issues, in addition, if not met, can alter the behavior, use or performance of an AI system and thus put its security properties at risk and be exploited by malicious third parties. The European Union launched its new Cybersecurity Strategy on December 2020 in order to enforce Europe's collective resilience against cyber threats. Later, on December 2022, an update of the Directive on the security of Networks and Information Systems came into force (NIS 2 Directive) strengthening security requirements for companies, addressing the security of supply chains and the supply chain cybersecurity for key information and communication technologies and establishing a basic framework with responsible key actors on coordinated vulnerability disclosure for newly discovered vulnerabilities across the EU (europa.eu, Digital Strategy). A cyberattack can have cascading effects with long-lasting negative impacts impeding the pursuit of economic activities in the internal market and thus generating financial loss (undermines user's confidence and causes major damage to the Union's economy and society) (Directive (EU) 2022/2555). Cyberattacks can influence AI-specific assets such as training data sets with data poisoning, trained models with adversarial attacks, or take advantage of vulnerabilities in the digital assets of the AI system or the supporting ICT infrastructure. High-risk AI systems providers should ensure a cybersecurity level and an appropriate ICT infrastructure. By achieving a harmonized set of such core requirements, the EU improves fundamental rights protection and provides legal certainty both for consumers and operators.

It was considered important to introduce a Union-level regulatory framework for trustworthy AI in order to avoid fragmentation of the Single Market into potentially contradictory national frameworks, preventing AI-embedded goods and services from free circulation (European Commission, 2021). A common AI regulatory framework will also protect all citizens and strengthen Europe's competitiveness and industrial basis in AI. People will trust AI and companies will benefit from the legal certainty. This people's trust will lead to higher demand

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for European AI products or services, especially high-risk AI systems should carry the CE marking in order to indicate their conformity with the aforementioned regulation and freely move in the internal market. Additionally, with the absence of cross-border movement barriers on AI systems, there is foresight for the AI single market to flourish. Limiting the characterization of high-risk AI systems to those having a harmful impact on the fundamental rights of persons in the EU, on health and safety, helps minimize any possible restriction to international trade, if any, and avoid unjustified ones.

In addition, in 2021 the EU proposed a revision of sectoral safety legislation such as on General Product Safety and Machinery Regulation. The General Product Safety regulation proposal update (2021) aims to modernize the general framework for the safety of non-food consumer products, preserve its role as a safety net for consumers, adapt the anticipation to challenges arising from new technologies and online selling, and finally ensure a level playing field for businesses. The proposal was about to, in most, replace the GPSD of 2001 (Directive 2001/95/EC on general product safety). GPSD started to be proved less effective in relevance with the e-commerce significant growth. Its application framework is wide since it is applied both in online stores and in brick-and-mortar shops. Though it is not enforced with concrete provisions in order to address the specificities of online selling, such as new actors appearing in the online supply chain. That weakness created, affected in a negative way both the safety of EU consumers and the level playing field for compliant EU businesses according to the EU assessment.

Regarding the new technologies, GPSD was not able to address the new challenges emerging. New risks appeared because of connectivity issues and questions arise regarding the applicability of the Directive to software updates and downloads, whereas when regarding an AI-powered product, its uncertain whether the directive may provide legal certainty for businesses and protection to consumers. The proposal, additionally, ensures that there will be

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greater consistency between harmonized and non-harmonized products in the EU and that it strengthens the protection of European consumers' health and safety and promotes their right to information. This is achieved by aligning the rules controlling market surveillance of non-harmonized products, i.e. products outside the scope of the EU harmonization legislation, with products being under the scope of the EU harmonization legislation.

The Machinery Regulation (Directive 2006/42/EC of the European Parliament and of the Council of 17 May 2006 on machinery) update proposal (2021) is in line with the EU's Artificial Intelligence policy and proposed regulation. It is also in line with the EU's policy on cybersecurity and links with future cybersecurity schemes pursuant to Regulation (EU) 2019/881 for the purpose of demonstrating compliance with the future regulation on machinery products. The proposal deems there is a need to redefine first clearly the notion of "machinery" whereas presenting a list of thirty-two more words referred to in the proposal for clarification and accuracy reasons. The Machine Regulation had to be revised due to the gaps it had regarding new technologies and aimed to tackle the following problems i) insufficient coverage of new risks originating from emerging technologies, ii) legal uncertainty due to a lack of clarity on the scope and definitions and possible safety gaps in traditional technologies, iii) insufficient provisions for high-risk machines (dedicating a specific part of the proposal defining high-risk machines), iv) monetary and environmental costs due to extensive paper-based documentation, v) inconsistencies with other pieces of Union product safety legislation and vi) divergences in interpretation (it was Member States' responsibility to choose the means to comply with the legislation and that led to different interpretations creating legal uncertainty and lack of coherence throughout the single market) and divergences to transposition (some Member States delayed transposition).

The Data Governance Act is a cross-sectoral instrument that entered into force on June 2022 and will be officially applicable from September 2023 being a key pillar of the European

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Strategy for data. It has been deemed necessary to improve data sharing in the internal market in order to leverage the economic and societal potential that data can return to the Union. The Act's purpose is for European citizens and businesses to benefit in the field of health, finance, mobility, environment, agriculture, public administration and skills, by facilitating data sharing through building trust among citizens and businesses, increasing data availability and overcoming technical obstacles regarding the reuse of data. Development is considered a result of better policy application. Data-driven decisions will result in efficient outcomes in all aforementioned sectors. The society will benefit from better solutions to the challenges it faces and businesses will benefit from the reduction of the costs that accompany data acquiring and processing.

Through four broad measure frameworks, the EU aims to boost reliable data exchange and establish domain-specific common European area data spaces for data-sharing and data-pooling creating a borderless digital internal market and a human-centric, trustworthy and secure data society and economy. These frameworks constitute:

a) Measures to facilitate the re-use of certain data categories held by public sector bodies, excluding personal and commercial confidential data, charging reasonable fees.

b) Measures for data intermediation services (data intermediaries such as data marketplaces are provided by Big Tech platforms having a high degree of market power due to controlling large amounts of data). These measures will ensure that intermediaries will operate in a credible manner within the common European data spaces performing neutrality and transparency. Data Intermediaries should be structurally (i.e. legally) separated from any other service provided. In addition, the commercial terms for data provision services, including pricing, should not be linked with the potential use of other services and all data and metadata acquired should be used only for reasons of data intermediation services enhancement.

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c) Measures enabling citizens' and businesses' own data-sharing for public interest reasons (data altruism). This is fulfilled by giving consent or permission to be used for such a purpose.

d) Measures facilitating the data sharing across sectors, by consisting of a European data Innovation Board advising via best practices in all aforementioned fields, and also facilitating the data transfers internationally increasing the EU's international competitiveness and own economic growth.

Another step towards digital enforcement in the EU has been the signing of the European Declaration on Digital Rights and Principles. The Declaration contributes to and is based on past initiatives related to the digital firmament (Tallinn Declaration on eGovernment, Berlin Declaration on Digital Society and Value-based Digital Government, Lisbon Declaration – Digital Democracy with a purpose) whereas it builds on primary EU law (the Treaty on European Union, the Treaty on the Functioning of the European Union, the Charter of Fundamental Rights of the EU), on secondary law and the caselaw of the Court of Justice of the EU and also complements the European Pillar of Social Rights. The goal of the Declaration is to share the political intentions and commitments at the highest possible EU policy level. According to this, the digital transformation inside the EU will take place while strengthening at the same time the human dimension of the digital ecosystem with the Digital Single Market at its core. The Declaration consists of six chapters each which respectively enshrines the following principles a) putting people at the center of the digital transformation, b) supporting solidarity and inclusion through connectivity, digital education, training and skills, fair and just working conditions and access to digital public services, c) restating the importance of freedom of choice and a fair digital environment, d) fostering participation in the digital public space, e) increasing safety, security and empowerment in the digital environment, in particular for young people and f) promoting sustainability. The Commission will keep track of the changes and development made in the field in relevance with the Declaration on an annual basis via the

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"State of the Digital Decade" report while the aforementioned commitments will guide the EU in its international relations according to the respective published press release (European Commission, 2022).

The EU's continuous effort in filling up the gaps in digital regulation has led it to launch the Digital Services Package, proposed by the European Commission in December 2020 and officially came into force in November 2022. The Digital Services Package is the first comprehensive rulebook for the online platforms on which people's lives highly depend according to the European Commission's respective press release after the adoption of the package by the European Parliament. The Digital Services Package is a single set of rules with two axes applying across the EU and concerning cumulatively a broad category of online services ranging from simple websites to internet infrastructure services and online platforms. More precisely, the package is composed of the Digital Services Act (DSA) and the Digital Markets Act (DMA) (European Commission, 2020).

The rules concerning the DSA primarily define clear responsibilities to providers of online intermediary services and, in particular, platforms such as online marketplaces, content-sharing platforms, app stores, social networks, and online travel and accommodation platforms. The DSA includes due diligence obligations applied to all digital services in the EU linking consumers to goods, services, or content. It includes comprehensive protection for users' fundamental rights online and new procedures executing faster removal of illegal content, goods and services online, activating a mechanism for users to easily flag such content and for platforms to cooperate with the users that will be having the "trusted flagger" tag. An additional set of measures will empower users and civil society and via also transparency obligations for the online platforms e.g. platforms to make available the algorithms used for recommending content or products to users. Very large online platforms (VLOPs) and very large online search engines (VLOSEs) are obliged to take risk-based actions in order to prevent possible misuse of

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their systems and to undergo independent audits of their risk management systems. There are also introduced mechanisms to quickly and efficiently adapt in reaction to crises affecting public policy security or public health whereas the European Commission pays special attention to the VLOPs by introducing an enhanced supervision and enforcement framework.

The obligations of the online intermediary services depend on their role, size and impact on the online ecosystem. In particular, it concerns *intermediary services offering network infrastructure: Internet access providers, domain name registrars, hosting services such as cloud computing and web hosting services, very large online search engines with more than 10% of the 450 million consumers in the EU, and therefore, more responsibility in curbing illegal content online, online platforms bringing together sellers and consumers such as online marketplaces, app stores, collaborative economy platforms and social media platforms*, *very large online platforms, with a reach of more than 10% of the 450 million consumers in the EU, which could pose particular risks in the dissemination of illegal content and societal harms* (European Commission, 2022). Currently, there is non-binding guidance to help online platforms and search engines, under the scope of DSA, to report user numbers in the European Union by the end of February 2023. This is about guidance that the European Commission aims to give to assist them with the provisions of the DSA. If the platforms' user number exceeds 10% of the EU's population, i.e. over 45 million users, the Commission will classify them as VLOPs or VLOSEs and thus be subject to additional obligations (e.g. produce a risk assessment, take risk mitigation measures).

Some large platforms have *emerged as gatekeepers in digital markets*. This characterization is valid due to that they control important ecosystems in the digital economy such as online marketplaces, operating systems, cloud computing services, online search engines, video-sharing platform services, number-independent interpersonal communication services, virtual assistants, web browsers, financial services and online advertising services. This fact gives

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them the *power to act as private rule-makers* resulting sometimes in the creation of unfair conditions for businesses acting through them and giving limited choices to consumers. Due to the online intermediation services may take multiple forms, the definition of core platform services, as mentioned in the DMA, should be technology neutral and should be understood to encompass those provided on or through various means or devices.

The Digital Markets Act (2022) *comprehensively regulates the gatekeeper power of the largest companies* and, as the DSA also does, creates a mechanism of rapid compliance with concrete obligations. The DMA complements and enforces the EU and national competition law with new rules and gives the Commission the power to carry out market investigations for checking the right implementation of the regulation in the continuously changing digital market landscape. Finally, *the Commission will be able to impose penalties and fines of up to 10% of a company's worldwide turnover, and that may, in the event of repeated infringements, reach up to 20% of such turnover. In the case of systematic infringements, the Commission will also be able to impose any behavioural or structural remedies necessary to ensure the effectiveness of the obligations, including a ban on further acquisitions relevant to the infringement.*

ii. The EU approach to Pricing Algorithms

The European Union is one of the largest e-commerce markets in the world based on Eurostat data (European Commission, 2017). According to the survey 53% of the respondent retailers track the online prices of competitors, out of which 67 % use automatic software programs for that purpose. Larger companies have a tendency to track the online prices of competitors more than smaller ones. The majority of those retailers that use software to track prices subsequently adjust their own prices to those of their competitors (78 %). Yet, back in 2017 when the survey

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was conducted, 87% of the retailers declared that they had not applied dynamic or personalized pricing.

The EU has not, so far, acted towards taking a specific approach regarding pricing algorithms, although has already encountered cases of algorithms operation. Pricing algorithms can be analyzed, to a large extent, by referring to the traditional reasoning and categories used in EU competition law (OECD, 2017). The EU considers cases where competition restraints can be enforced by the use of pricing algorithms and not autonomously beginning by the algorithms themselves. For example, Resale Price Maintenance (RPM) practices have been facilitated in the e-commerce sector by the blooming of online retailing and can be used to lessen the intense price competition by using algorithms to scrutinize the pricing practices of online retailers (see the EC's Asus case, AT.40465/2018, the Pioneer case AT.40182, the Danon & Marantz case AT.40469 and the Philips case AT.40181 (Colangelo, 2021)).

The European Commission (EC) took five infringement decisions to prohibit RPM in the online stage. The EC, in order to support its condemnation, relied upon the "by object" characterization of fixed or minimum RPM under Article 101(1) of TFEU, a move considered as an old-school skepticism within a very modern market context (use of algorithms in e-commerce). Though, the EC's approach becomes more dubious when seen under the recent case law framework that considers as most important the legal and economic context of any restraint (Dunne, 2020). Another algorithm-related case, elaborated by the European Commission, is Google Search (Shopping) (AT.39740). Google's general search algorithm consisted of two interlinked modifications, a) *tweaks to ensure that Product Search would receive more prominent placement than the objective quality of the service might otherwise deliver*, and b) *the application of "adjustment algorithms" to competing comparison shopping products which had the effect of demoting those competitors* (Dunne, 2020). That conduct constituted an abuse of dominance.

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Nevertheless, the EC improves its regulation in order to tackle more possible competition restraints as did with the Guidelines on Vertical Restraints (2022). According to this, online intermediation services lose their *safe harbour* because providers of these services when having a hybrid function may also have the incentive to favor their own sales and the ability to influence the outcome of competition between firms that use their online intermediation services (Heinisch and Hofmann, 2022). Though, the EU has currently faced a complaint regarding the algorithm that determines European electricity prices. The complaint was towards the Austrian antitrust regulators supporting that the algorithm used hinders competition on European power exchanges and keeps the prices high.

There is a demand for the code for the Pan-European Hybrid Electricity Market Integration Algorithm to be published in order to detect whether there is a "tacit and indirect through software or price algorithms" agreement. *The complaint attacks the design of the electricity market which* the lawyer (that demanded the respective investigations) Georg Zanger, said it is *fundamentally anti-competitive and hikes the price for green energy* (Fiedler, 2022).

iii. General Data Protection Regulation (GDPR) and AIA pricing

Data protection within the EU is based on the Article 16 TFEU[12] and further protection is offered by the Charter of Fundamental Rights of European Union and the General Data

[12] Article 16 TFEU:
1. Everyone has the right to the protection of personal data concerning them.
2.The European Parliament and the Council, acting in accordance with the ordinary legislative procedure, shall lay down the rules relating to the protection of individuals with regard to the processing of personal data by Union institutions, bodies, offices and agencies, and by the Member States when carrying out activities which fall within the scope of Union law, and the rules relating to the free movement of such data. Compliance with these rules shall be subject to the control of independent authorities.

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Protection Regulation (Gorecka, 2020). The is a set of rules to protect individuals when their data is being processed by the private sector and most of the public sector. With these rights' enforcement, individuals are able to better control their personal data and businesses can benefit from consumers' trust. GDPR stipulates three types of data, a) personal data, b) pseudonymous data and c) anonymous data. Though, anonymous data are ignored (Li, 2022). According to the Regulation (2016/679), *the principles of data protection should therefore not apply to anonymous information, namely information which does not relate to an identified or identifiable natural person or to personal data rendered anonymous in such a manner that the data subject is not or no longer identifiable.*

As more as price discrimination becomes personalized, the welfare shifts from consumers to suppliers since it places consumers in smaller and more homogeneous segments, charging them a price closer to their willingness to pay (Poort, 2021). Personalized pricing is considered to pose a threat to privacy and non-discrimination fundamental values. Algorithmic pricing usually satisfies the definition of personal data as sellers generally set prices after collecting users' IP addresses, cookies and sometimes geo-location data (Li, 2022). Even though personal data are protected by the relevant data protection law (data protection law can hopefully regulate online personalized pricing by indirectly controlling personal data usage and preventing the data subject from being subject to algorithms), anonymous data (which are not) seem to play a respectively important role in personalized pricing. Anonymous data or else affinity data cannot be classified as personal since no specific user is linked to them. Algorithmic pricing can be successfully achieved through only anonymous data. The progress of technology and the large volume and availability of Big Data can enforce algorithms to

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The rules adopted on the basis of this Article shall be without prejudice to the specific rules laid down in Article 39 of the Treaty on European Union.

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extract more sensitive information. *For example, users' location, age, and other preferences can be inferred only by their mobile communication patterns* (Li, 2022).

There are sound pieces of evidence that affinity-based algorithmic pricing can elude the data protection law. On the other hand, the EU's primary and secondary legislation regarding online algorithmic pricing, including the EU Charter, the IP law, and the trade secret law pose potential hurdles to the implementation of GDPR, according to Li (2022).

6.2.2. North America

i. United States of America and AI

In 2020 the United States of America launched the National AI Initiative of 2020 which then became law on January 1, 2021. The main goal of the initiative was a) to ensure continued US leadership in Artificial Intelligence and Research and Development, b) be the guide of the world in the development, c) use trustworthy AI systems in public and private sector, d) prepare the present and future US workforce for the integration of artificial intelligence systems across all sectors of the economy and society and f) coordinate ongoing AI activities across all Federal agencies, to ensure that each informs the work of the others (NAII, 2020).

On February 2022, U.S. Senator Ron Wyden, D-Ore., with Senator Cory Booker, D-N.J., and Representative Yvette Clarke, D-N.Y. introduced the Algorithmic Accountability Act (AAA) of 2022. This is described as a landmark bill to bring transparency and oversight of algorithms, software and other automated systems that are utilized in almost every aspect of American's

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lives (Wyden, 2022). Based on this bill, firms using or selling automated decision systems to make critical decisions are obliged to conduct impact assessments for bias, effectiveness and other factors. Additionally, it is the first time a public repository at the Federal Trade Commission (FTC) of these systems is created, adding also fifty staff to the FTC in order to enforce the law (US, 2022).

According to OECD (2022), several federal agencies are using existing powers to regulate AI systems. For example, the White House's Office of Science and Technology Policy (OSTP) is formulated an AI Bill of Rights and the Equal Employment Opportunity Commission (EEOC) has launched an Initiative on AI and Algorithmic Fairness. The FTC (which enforces key consumer protection laws like the Fair Credit Reporting Act (FCRA)) and the Equal Credit Opportunity Act (ECOA), is expected to significantly increase its oversight and enforcement of AI system use. Furthermore, in order to enforce among others the combat against misused AI, the US and EU established the Trade and Technology Council in 2021 and identified the field of AI as a priority for coordination and cooperation (Hamilton, 2022).

The White House Office of Science and Technology Policy (OSTP) published the Blueprint for an AI Bill of Rights in October 2022 (Lee and Malamud, 2022). The AI Bill is a non-binding roadmap for the responsible use of AI, identifying five core principles and associated practices for the effective deployment of it (Safe and Effective Systems, Algorithmic Discrimination Protection, Data Privacy, Notice and Explanation, Human Alternatives/Consideration and Fallback) (The White House, 2022). Assessing the bigger picture of the AI Bill of Rights *is a welcome initiative that must be rightly situated in the context of other forthcoming initiatives* (Firth-Butterfield et al., 2022). Although these initiatives by the White House are influential and are perceived as an encouraging first step, are also criticized as weak in front of the challenges that AI systems emerge. Thus, further action toward respective legislation is needed (Lee and Malamud, 2022).

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6.2.3. Asia

i. People's Republic of China and AI

China has launched 22 policies from 2017 to 2022. The National AI Strategy "National New Generation AI Plan" came into force in 2017. The strategy includes initiatives and goals for R&D, industrialization, talent development, education and skills acquisition, standard setting and regulations, ethical norms, and security. The Plan's main objectives, based on a three-step strategy, were to a) make China's AI industry "in-line" with competitors by 2020, b) reach "world-leading" in some AI fields by 2025 and c) become the "primary" center for AI innovation by 2030. By 2030, the Chinese government aims to cultivate an AI industry worth RMB 1 trillion (EUR 130 billion), with related industries worth RMB 10 trillion (EUR 1300 billion). China envisaged to have become, by then, a global center for AI technologies and AI economy with a deep and integrated IP application in any production segment, social governance, and national-security and defense. Furthermore, the Chinese government partnered with national tech companies to develop research and industrial leadership in specific fields of AI and was about to build a USD 2.1 billion (EUR 1.8 billion) technology park for AI research in Beijing (OECD, 2022).

According to Stanford University's AI Index on global AI advancements across various metrics, China ranked in the top three countries for AI vibrancy (Chen et al, 2022). For example, in 2021, China produced one-third of both AI journal papers and AI citations worldwide. McKinsey's research supports that there is a tremendous opportunity for AI growth in new sectors in China. Especially in sectors where China's spending on innovation and R&D traditionally lagged global counterparts (e.g. logistics, transportation, automotive,

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manufacturing, healthcare) there will be clusters where AI use could create more than $600 billion (economic value) annually.

On January 2022, China adopted the regulation "Provisions on the Management of Algorithmic Recommendations in Internet Information Services". The regulation is the result of an initial draft produced by the Cyberspace Administration of China (CAC) in August 2021 with the purpose to regulate algorithms and especially "recommendation" algorithms such as those used in online stores, content services, search filters and social media (ai-regulation.com, 2022) The new algorithm provisions are evidence that CAC envisages to play a critical role in antitrust regulation fostering industry competition (Huang, 2022). In the provisions document, there is the new Article 15 which is a response to the dominance of monopolistic tech giants. The Article bars the covered providers from using algorithms to "unreasonably" restrict other internet information service providers or block and sabotage the normal operation of the internet information services they lawfully provide (Webster, 2022).

6.3. International Organizations Action on AI

The Organization for Economic Co-operation and Development (OECD) promotes the use of innovative artificial intelligence provided it is trustworthy and respects human rights and democratic values. It has so far dedicated many resources to building a stable policy environment and fostering the trust in and adoption of AI in society at the international level. In accordance with this view, it published, in 2019, the AI Principles i.e. a set of practical and flexible standards of AI so that they can be the base for any future innovation in the field. The OECD's AI Principles are divided into principles that are values-based and recommendations for policymakers. The Values-based principles cover the following axes, a) Inclusive growth with sustainable development and well-being, b) Human centered values and fairness, c) Transparency and explainability, d) Robustness, security and safety and e) Accountability.

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Regarding the recommendations for policymakers, these are oriented towards advices on a) investments in AI and R&D, b) the fostering of a digital ecosystem exclusively for AI, c) the provision of an enabling policy environment for AI, d) building human capacity and preparing for labour market transition and e) the international cooperation for trustworthy AI.

OECD also established the Working Party on Artificial Intelligence Governance (AIGO) under the Committee on Digital Economic Policy (CDEP) in order to oversee its work on AI policy and bring together technical experts, industry and policy. AIGO is a policy observatory that among others reviews national policies on AI. AI is considered the biggest commercial opportunity in today's fast-changing business environment, while at the same time improving the lives of billions of people. It is projected that by 2035, AI will make organizations 40% more efficient, a percentage corresponding to $14 trillion in economic value (WEF, 2021). On the other hand, AI is also implemented in the collection of data from smartphones, sensors and consumers' habits that reveal much about society and for which few people have a say in how these data are created and used (ainowinstitut.org).

The concerns regarding AI implementation in all sectors raised the need for validation and standardization of AI, which is considered the number one research problem in the field. The International Organization for Standardization (ISO) as long as other organizations make efforts to develop AI-related standards in order to enable AI to provide efficient and trusted solutions. According to ISO (iso.org) applying a management system standard (MSS) will enable organizations to dynamically map their work to the regulatory and societal requirements captured through the MSS, will be a trust mechanism that will facilitate B2B contracting and will establish a baseline that can be verified through audit and/or conformity assessment. All three achievements will help manage AI uncertainties efficiently. Other initiatives on the global level are the United Nations' Educational, Scientific and Cultural Organization (UNESCO) adoption of a standard-setting recommendation on AI ethics and the multistakeholder initiative

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of the Global Partnership on Artificial Intelligence (GPAI) which brings experts to support "cutting-edge research and applied activities on AI-related priorities" (OECD.ai). In addition, the RAII (Responsible Artificial Intelligence Institute) contributing to the international effort to manage AI developments, mapped over 200 AI-related international principles and policy documents. This collection updated RAII's Implementation Framework, a framework setting out requirements and a suite of questions to evaluate AI systems upon globally agreed principles. The RAII is the only global and member-driven non-profit dedicated to enabling successful and responsible AI efforts in organizations (responsible.ai). A certification program enabling organizations to certify the conformity of their AI systems with the appropriate ISO standard is as well developing by RAII. (OECD.ai).

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Conclusion

The enhancement of computing power and connectivity across the globe has significantly contributed to the rapid evolution of digital markets. The deployment and consequent inclusion of machine learning pricing algorithms in digital sales features as a necessary management asset without which the presence of agents in certain marketplaces is impossible. Moreover, it is vital to remember that entire markets are built upon pricing algorithms, reminding us that pricing based on machine learning technics, and even neural networks, will prevail and evolve even more along with the supporting technology and the innovation this incorporates.

Despite several scientists' views on the improbability of collusive equilibria to arise by the algorithms' autonomous behavior in real market conditions, one cannot ignore the existence of an empirical study and several experimental ones proving the opposite. Even in the case of the laboratory environment where experimental studies control several parameters, their results could be modestly viewed as indicative of a tendency in these markets. It cannot also be ignored that AI can exhibit unobserved data-processing procedures and consequently decision-making where only final actions are observable. This is referred to as a black box since the decision-making process design is not observable. On the contrary, only inputs and outputs are known. Deep-learning technics already power many of the useful applications someone uses in her portable device on a daily basis and, of course, AI in its finest operation, such as DQN, creates the potential for exciting discoveries in fields such as climate science, physics, medicine, and genomics (as Dharshan Kumaran and Demis Hassabis of Google's DeepMind stated in a blog post under the title "From Pixels to Actions: Human-level control through Deep Reinforcement Learning"), and besides, on the capabilities of

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DQN, let us not forget that beating the human champion at the GO game is considered as one of AI holy grails (Stucke and Ezrachi, 2017).

It is obvious that the algorithmic tacit collusion problem gives rise to a new field of scientific interest and attracts antitrust authorities' attention. It is considered that, hereafter, there is a need to apply very precise measures and use tools that will tackle collusive behaviors or prevent them from happening. The first and most important issue is for someone to understand the risks of algorithmic collusion and the mechanisms supporting it. Second, tools that can be applied include auditing the pricing algorithm (alternatively, algorithms could be activated in a "sandbox" where their effects could be observed and then assessed), intervening with market or sector investigations, and targeting the "abuse" of excessive transparency, probably where clear anticompetitive intent is present. Third, competition agencies could begin commissioning experiments with pricing algorithms and conduct merger reviews, and target the firms' discount rate (collusion, tacit or express, is sustainable "if and only if firms put sufficient weight on future profits, i.e., if their discount factor is not too small) (Stucke and Ezrachi, 2017). Accordingly, more experimental work especially replicating real-world circumstances, and not under the delimiting laboratory environment, is needed in order to reveal further algorithmic operation characteristics. The computing power problem still poses strong boundaries in a representative replication. Though, consumer-relevant platforms providing product prices comparisons, statistical analyses of price trends, and product reviews constitute a counterweight for consumers surplus.

From a broader point of view, AI-related policies across the globe constitute a sound movement against unsupervised AI-related software and machines that may severely threaten society in terms of democracy, security, safety, fundamental human rights, and

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the economy. Regulating AI is a breakthrough achievement as AI is still a new and continuously evolving technology. International cooperation, both concerning states and organizations and competition authorities, is considered crucial, due to the fact that AI emergence is not solely an issue of technology but also relates to other fields and thus needs a harmonious and collective interdisciplinary approach.

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