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"AI and price setting mechanisms: a literature review "

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Sommario

Introduction 4

1. Literature review basics 7

1.1 What is Artificial Intelligence 7

1.2 A short history of Artificial Intelligence 9

1.3 Artificial Intelligence nowadays 11

1.4 Artificial intelligence and pricing 17

1.6 Q-learning 21

2. Artificial intelligence as supra-competitive price facilitator 24

2.1 Price as result of reward and punishment path 24

2.2 How different price algorithms may impact on prices 29

2.3 Artificial intelligence impact in the monopoly market setting 33

3. Artificial intelligence as competitive price facilitator 38

3.1 The impact of algorithm-based demand prediction on pricing strategies 38

3.2 Players' communication through artificial intelligence and effect on prices 42

3.3 Learning-paradigms differences may influence price outcomes 46

3.4 Different pricing outcome between algorithms' adopter and non-adopters 52

4. An alternative perspective 56

4.1 Possible price setting mechanisms resistance to artificial intelligence 56

4.2 Empirical evidences on the absence of artificial intelligence for price setting mechanisms 58

BIBLIOGRAPHY 66

SITOGRAPHY 69

LIST OF FIGURES

Figure 1: summary scheme of the literature review work

Figure 2: private investment in ai by geographic area, 2013-2021.

Figure 3: private investment in ai by focus area, 2020-2021

Figure 4: number of ai publication in the worlds, 2010- area, 2020-2021.

Figure 5: top contract spending on ai by U.S government department and agency, 2021.

Figure 6: number of ai-related bills passed into law in 25 selected countries, 2016-2021

Figure 7: number of publications on ai in e-commerce per year, 1991-2020.

Figure 8: the machine learning process

Figure 9: machine learning functionality and process flow

Figure 10: two firms' price behavior after defection

Figure 11: example time series of prices for identical products across retailers

Figure 12: heterogeneity in pricing technology by one hour of the week

Figure 13: price and quantity under certainty

Figure 14: price and quantity under certainty and under uncertainty

Figure 15: Miklos-Thal and Tucker's intuition framework

Figure 16: Ulrich Schwalbe's work structure

Figure 17: price path with different algorithm designs

Figure 18: price outcome with different algorithms design - synchronous updating

Figure 19: price outcome with different algorithms design - asynchronous updating

Figure 20: estimated probability of observing, for each day of stay, at least a price variation over the booking period – by star classification

Introduction

The usage of artificial intelligence is a very hot topic at the moment.

More and more are the implementations of algorithms and, particularly in this historical moment, they are evolving at incredible speed and across different industry.

More particularly, its spread and its effects can be visible at different level: starting from the macro-economic environment and ending up at a business level.

In fact, one of the main features of the artificial intelligence tool is how easily they permeable in different contests.

From a macro-economic point of view, artificial intelligence, with its different facets and different implementations are strongly attracting investments.

In this sense, according to International Data Corporation (Idc), the cumulative public expenditure in artificial intelligence research will increase from 83,5 billions of dollars (in 2021) to 204 billions of dollars in 2025. It's expected CAGR, between last year and 2024, is predicted to be 24,5%, one of the highest across industries taken into consideration by the Idc.

Of course, these investments' impact will be tangible later in comparison with effect AI is already having at micro-economy and corporate level.

In fact, the implications that artificial-intelligence-related technologies are having on firms can be considered definitely relevant, already from years.

For example, in 2016, there were a very strong presence of chat-bots within firms and their presence grew drastically due to their added value in business models and in pricing suggestions.

This, in turns, implies a huge structural change of different companies, of the way they compete in different sectors and, consequently, for consumers.

In this sense, at the moment, it is difficult to have a totally clear picture of when and how the use of algorithms can impact the well-being of consumers.

That said, what is certain is that the degree of investment, the amount of innovations and the continuous increase in the use of artificial intelligence in the various markets has attracted the attention of institutions.

The incredible capillarity of these new tools has begun to question governments and regulatory bodies on what the consequences of an abuse of artificial intelligence can be, from an economic, legal and ethical point of view.

At present, from what emerges from reports, papers, articles and press, we can see a strong pessimism regarding the anti-competitive function of these new tools.
This widely shared point of view emerged mainly due to the impossibility (or the great difficulty) in attributing to a subject the responsibility for actions that have an impact at the level of competition and welfare.
However, the fact that there is no practical evidence of this type of price activity and the strong attention of the institutions, however, intrigued me.
For this reason, it seemed useful to me to take stock of the situation to understand if actually the increase in attention with respect to the use of AI for prices, is something well founded.
In particular, I wanted to pay attention to whether and how solutions that use algorithms can convey market agents in their pricing choices: it is clear that companies, from an operational and functional point of view, have important advantages deriving from the use of AIA solutions. What is not clear is whether and how this type of innovation can affect prices.
In this sense, given the absence, I thought it was useful and interesting to collect the different points of view on the subject to build a review of the available literature.
surprisingly, the amounts of articles, working papers and books on the subject turned out to be quite poor. This didn't actually surprise me for a simple reason: the issue, albeit current and in strong growth, has so far had little practical feedback due to the lack of propensity to disclose information relating to pricing strategies. This, according to the evidence from the review I propose, is a disincentive factor for research on the subject.
Despite this, the strong innovative impact and the effective attention on the part of numerous stakeholders, has however intrigued a rather large number of curious, scholars and enthusiasts on the subject to try to give an academic direction to this phenomenon.
This led me first of all to do a first screening of the literature based on their publication date.
Given the rapid advancement of the technologies in question, I thought, in order to give an updated and a consistent interpretation as possible, to consider works from 2018 onwards.
This type of screening allowed me first of all to streamline the groups of papers, to group them according to different points of view but not to lose all the literature cited in the papers considered.
This allowed me, quite clearly, to be able to divide the literature into three main points of view.
The first, supported by a relatively large number of scholars, embraces the idea that AI can support companies in sustaining supra-competitive prices.
The second, also supported by a consistent group of authors, is based on the idea that the use of algorithms can lead companies to compete at competitive prices.

A third point of view seems, instead, to be quite pessimistic concerning the real pervasiveness of the AI, at least for a pricing activities' point of view.

Below, I insert a graphical representation of the general work I realized on this fascinating topic.

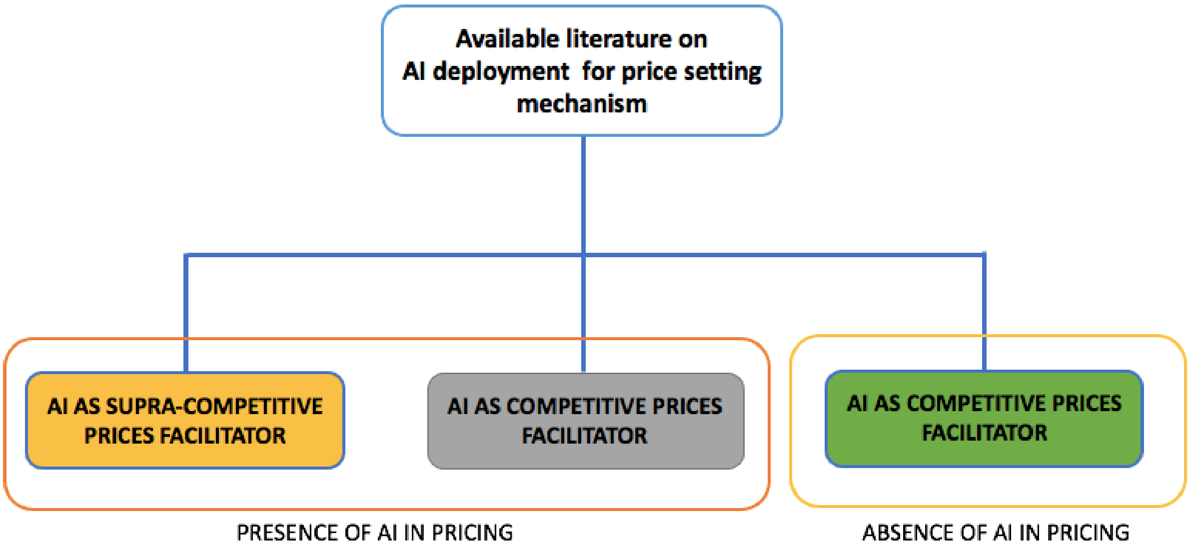


Figure 1: summary scheme of the literature review work

The review of the literature I propose is therefore a way, net of the status of the literature on the subject, to be able to offer the reader not only an updated set of papers on the subject, but also an interpretation of the phenomenon divided into three main pillars: two of them, even if under different and opposite paradigm, suggests the presence of AI in pricing mechanism. The other, on contrary, is a new emergent perspective that emphasizes the absence, or at least the very poor impact of algorithms in pricing decisions.

The aim therefore is to develop a work that can be read by anyone, that can excite and that can be an instrument for further developments on the topic.

1. Literature review basics

1.1 What is Artificial Intelligence

Today, like never before, artificial intelligence is one of the most discussed and used word by technicians in the IT sector, but not only.
AI (artificial intelligence) is widely spread in different industries and has taken place in heterogeneous way in different industries.
It can be safely stated that we experience it in every item, transaction and tool that has enough technology to support data production and elaborate it: from information services to medical devices.
AI is currently something that surrounds us and the main concern about scholars and legal/regulatory bodies is how and if we can fully control for it.
In some cases, in particular when explicit, we can control for it (like when we need to translate a phrase on Google translate and the algorithm suggests us a correct translation) while, in other cases, it is something that we do not control (like when we receive notification on a particular topic related to an article we red time ago), and this surprises us.

AI cannot be seen and interpreted, at least from a technical point of view, as a "super-intelligence", a pre-set cyber brain or a system that is perfectly designed in IT (information technology) labs.
AI, in particular, is a particular niche field of computer science in which computer scientists design and organize the software and hardware parts for complex systems, such as robots and complex hardware.
It means that, this "new"[1] and fascinating part of the computer science, is able to give to a machine, robot, automatic and/or semi-automatic systems some characteristics that "seems" to be related to human activities, like thinking, reasoning and providing solutions, quickly.
More precisely, it is incorrect, in fact, just to talk about a generic intelligence. On contrary, it is correct to discuss about a peculiar part of the intelligence: the prediction.
To make a first example to better frame the point of discussion, we can take under analysis Alexa, the intelligent personal assistant design in 2014 by Amazon. The little speaker has

[1] As it will be furtherly discussed, AI is a new world but, in reality it has quite remote origins

different AI capabilities and can be fully connected with home automation devices. In particular, the device is able to receive a voice input and can restitute an action (answer) to the user.
When this happens, Alexa does not "think" to an answer to give. It is not able to do this, due to the fact it has not a "pure" intelligence. It does not know what is the temperature in Colorado (when asked for it).
It, instead, uses huge amount of accessible data to predict a proper answer to a question/input. It analyzes the sequences of word produced by the user, and, according to its data-driven software and the usage of wi-fi connection, it delivers an answer based on a pure and fast prediction.
Of course, at least at current technological stage, AI can make mistakes.
If the answer given is not correct, the machine recognizes the mistake, "learns" from it and produces another result. If this result it is not correct again, this creates a "self-improvement loop" that, during the time and a given data accessibility, it improves the quality of the answers, what we call accuracy.
This, today, is put in place at an extraordinary speed.
For this reason, the interesting question related to this process is then to understand the amount of data that each machine needs and the amount of time needed to properly process the different inputs.
Currently, the volume of data is huge and, with quite consistent differences among countries[2], it is increasing in quantity and improving in quality.
For what concerns the time for processing these data, we can safely state that the time needed to elaborate inputs is decreasing importantly, with still improvement margin.
Of course, the importance of such argument arose the attention of different stakeholders and lot of different new AI's perspectives and the trade-offs need now be taken into consideration.
In fact, for example, common questions that are now overcrowding the regulatory bodies and the governments' agenda are if the usage of the "big data" necessarily mean less privacy or which should be the the autonomy that the AI machines have.
It is hard now to give a unique answer and, in my opinion, it's all a matter of finding a correct tradeoff, in every single situation and industry settings.

[2] The different regulation and jurisdiction among countries are regulating the data production and its supply in different way. This creates divergencies among data usage and the subsequent AI development. In fact, there are countries (like U.S and China) in which AI developments are much more consistent than in other countries.

During the rest of the work, I will try to explain, rather than convince the reader, how we can deal with these tradeoffs and to see the AI phenomenon in an updated and most complete way possible.

1.2 A short history of Artificial Intelligence

“Artificial intelligence” seems to be a modern, contemporary and maybe even futuristic way to say. The reality of the facts is that it is something that in practice has its birth long time ago. In the rest of this paragraph, I recontextualize the different phases that can help the reader to know how we got to talk about artificial intelligence and prediction today.

René Descarte, also known as Cartesio, is probably one of the most known and most famous philosophers and mathematicians of all time, definitely considered the founder of modern philosophy and mathematics. He did not, of course, spoke directly about AI but, he dwelt on important aspects concerning the relationship between "res cogitas" (the thought) and "res extensa" (the matter). In particular, therefore, the relationship that today can be recontextualized in the relation between software and hardware, algorithms and prediction machine.

Alan Turing, considered the father of information technology, was a great mathematician, cryptographer and philosopher. In more recent years, in 1950, just after the Second World War, in an article called “Computing machinery and intelligence”, he showed the “Turing test”, also know under the name of “The imitation game”. It is a method which is based on the presence of three actors: a person, a machine and another operator. It has been developed for demonstrating that a machine can be able to act in an “intelligent” way, for instance by distinguishing items, sex and other features among different options. Unfortunately, due to low memory capacity and high costs for the trial, it had not success but it interestingly gave visibility on the issues related to what we call today AI.

The next important milestone in the history of AI can be found 1956, in Dartmouth, New Hampshire. It is in this wonderful place that John McCarthy, an American notorious information technology scholar, organized a convention on the first “neural networks, computability theory, and natural language processing”[3].

In the “Dartmouth proposal”, the organization team mentioned and introduced for the first time, in an informal 17 pages letter, the word “Artificial intelligence”. In particular, recovering the

[3] https://it.wikipedia.org/wiki/Conferenza_di_Dartmouth

original “Dartmouth proposal”, at page 1, it can be red *“The study will proceed on the basis of the conjecture that, in principle, every aspect of learning or any other characteristic of intelligence can be described so precisely that a machine can be built that simulates them”* (J. McCarthy et al, 1955).

It is in this period of the history that the artificial intelligence, as a way to say as well as in primordial examples, started to spread in the globe. This is also due to the fact that, after the second world war, a lot of technologies used in the war were transversally deployed for the population and this helped to boost a period of technological innovation, across several field, IT included.
For example, in 1966, Eliza, the first chatbot (also known as chatterbot), made by Joseph Weizenbaum, was able to listen and memorize key words, predict an answer and produce a sound by which it was able to answer to some easy questions. This first example of prediction machine was not really accurate, and in fact it was not heavily used but, a lot of first videogames developers implemented its technology in very successful videogames (such us Adventure, the first interactive videogame).
The period between 1956 and 1973 has been called by the industry expert the “the first AI summer”: it is in this time span that big developments and progress took place in the IT industry. In fact, the market starts to be crowded by new small players and boutiques that, also due to an increasing scholars’ attention, started working on new machines and software. Unfortunately, again, as it happened in the past, due to financial assistance lack and still poor financial investor willingness, the industry had difficulties in grabbing the market.
The period between 1974 and 1980 has been recognized as the “first AI winter”. Interestingly enough, the industry has not been quickly recognized for its potential and, according to the “ups and downs” it had, we are in a safe position to state that it took quite a lot to exploit potential and to convince investors to bet on this industry.
In 1981 that Feigenbaum and some of his collaborators invented the first open-source system: this system was mainly deployed in companies, particularly to enhance the accuracy and the forecast of goods orders. From this moment on, several countries started to understand the potential implication of the AI in companies, thus in the economy of each country. Not surprisingly, one of the first country to leverage on this technology was Japan, well known place for passion and know-how concerning the lean management and lean production. US and other countries in Europe, like UK, started to implement these new technologies, pushing and hoping for an increase in industry’s relative competitiveness.

At this stage AI seemed poised and ready to take off, also given state investments. Unfortunately, once again, the industry had trouble in starting. The reason is due to the fact that new powerful devices made by new players (such as IBM and Apple) were stifling the advancement of other technologies: the new computers were faster, more reliable and "customer friendly". So, government investments in AI made by Japan and others were still unsuccessful at this stage.

So, the question is then: when did the AI start to break the market and how did we achieve the investment level that we have today? Is this just few year ago?

The answer, according to the majority of the scholars and industry expert is quite simple: in the ’90. Just before the new millennium, due to the empowerment of the calculation force (the one that Alan Turing missed after the Second World War), new advanced machine came out: a relevant event took place, in particular, in 1997, when “Blue deep”, an informatic software, won a chess match with the best player in the world, Garry Kasparov.

In the new millennium a lot of improvement occurred and this was also due to a massive investors’ effort, especially in some countries such as USA and China. The field of usage of the AI increase dramatically: we do not talk only about prediction of chess game actions or language translation. In the last decade, the AI has entered complex industrial contexts, such as the automotive one, health, safety and, obviously, financial contexts. We are talking about technologies that are able to predict the formation of cancer, downturns in the financial markets, collisions between vehicles and much more.

The real challenge to be faced, therefore, is certainly no longer technological. The current and future challenge is on an ethical and governmental level. The literature with respect to these two strands is in an embryonic state and governments are starting to dwell on these issues in order to counter (or maybe push) the usage of artificial intelligence. There is a lot of uncertainty in this industry at the moment but, of course, we can rest assured that the history of this fascinating industry is yet to be written. And we cannot predict it.

1.3 Artificial Intelligence nowadays

Last April, the University of Stanford released its annual report on the AI global environment. The report, directed by Jack Clark and Ray Perrault, highlighted several interesting aspects related to the new trends, opportunities and scenarios the AI is putting in place globally.

First of all, the AI industry, due to its intrinsic nature and to the general phenomenon of the industries’ consolidation, its changing importantly.

More in detail, taking as benchmark the 2020, the number of firms competing in this industry is importantly dropping: from 1051 in 2019 to 746 in 2021[4]. This phenomenon is representing a key market and performance indicator.

In particular, this decreasing-of-player trend is underlining a consolidation of the market that is heavily supported by the financial passionate. In this sense, the private investment in the AI industry doubled the amount reached in 2020, making a new record of investment in the industry of about 93.5 billions of dollars (by 15 investment round of 500 millions dollars in 1 year).

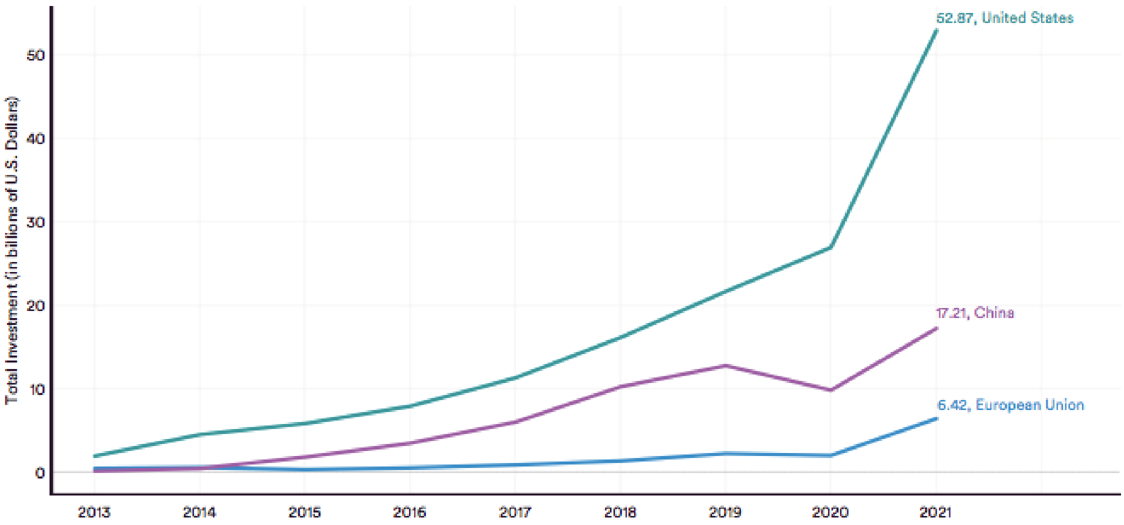


Figure 2: private investment in ai by geographic area, 2013-2021.

Source: NetBase Quid, 2021.

[4] "The AI Index 2022 Annual Report," AI Index Steering Committee, Stanford Institute for Human-Centered AI, Stanford University.

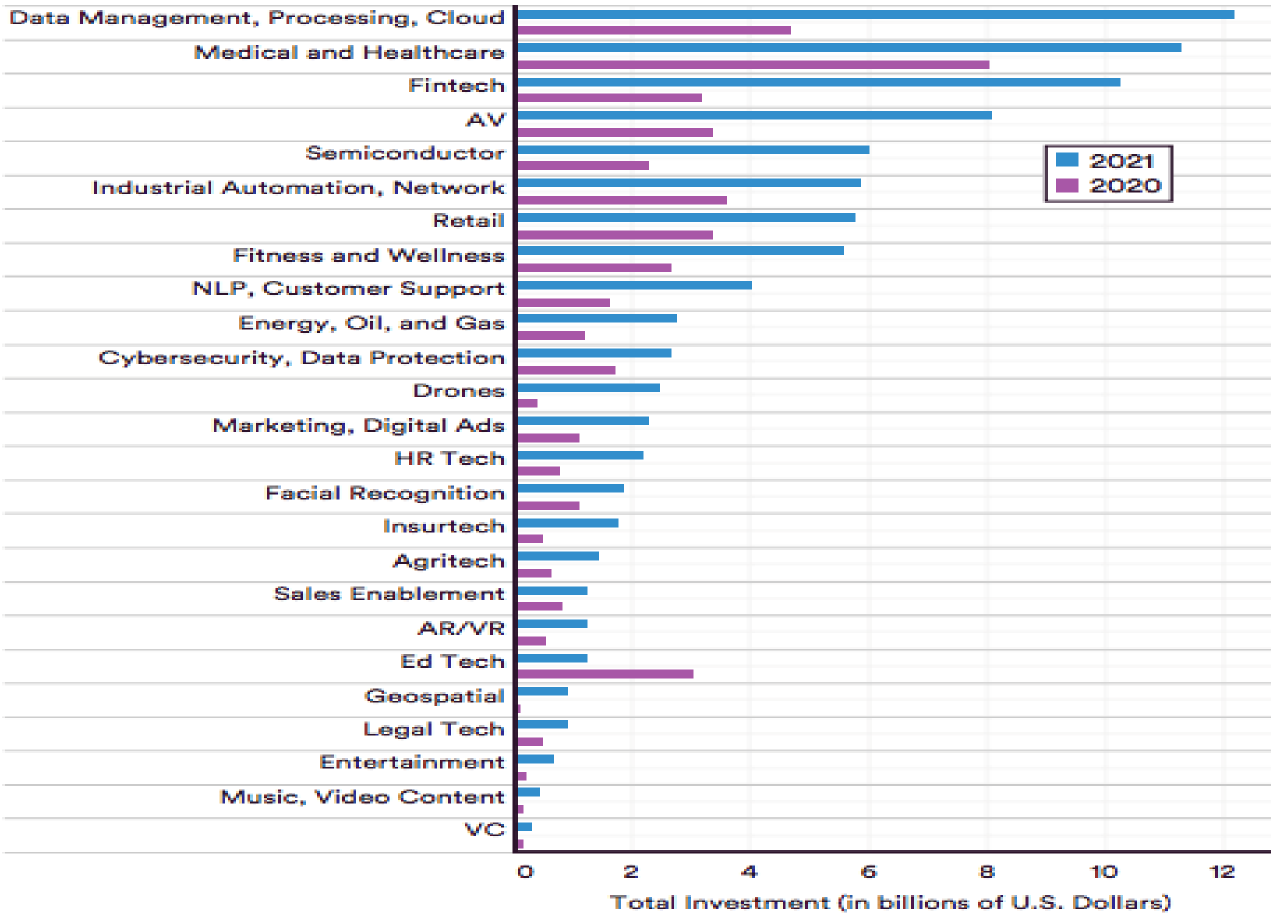


Figure 3: private investment in ai by focus area, 2020-2021.

Source: NetBase Quid, 2021.

A part the big private investments in the industry, the different countries are tackling their public expenditure to, from one side, sustain this this growing and profitable industry and, from the other side, to increase their strategic competitiveness and dependency in data production/supply. The two countries that are leading the AI industry expenditure are USA and China.

Currently, USA is definitely the artificial intelligence market leader with an expenditure of 5 billion dollars, followed by China that is going, in the next ten years, most probably, to match the Americans.[5] EU seems to follow back the two market leaders but with a lower rate of expenditure. This is for sure due to the fact that in EU data protection is very strong and the

[5]Agenda digitale. https://www.agendadigitale.eu/cultura-digitale/intelligenza-artificiale-a-che-punto-sono-i-competitor-mondiali-e-cosa-sta-facendo-lue/.

regulation around the accessibility of personal/customer/market information is very strict. This is representing a brake on important investments, both private and public[6].

Their effort in supporting the market of reference is also underlined by the number of literature publications on the general AI field: the number of working papers produced in China from 2012 grew by more than 30% in 2020 while, interestingly enough, in USA they fell[7].

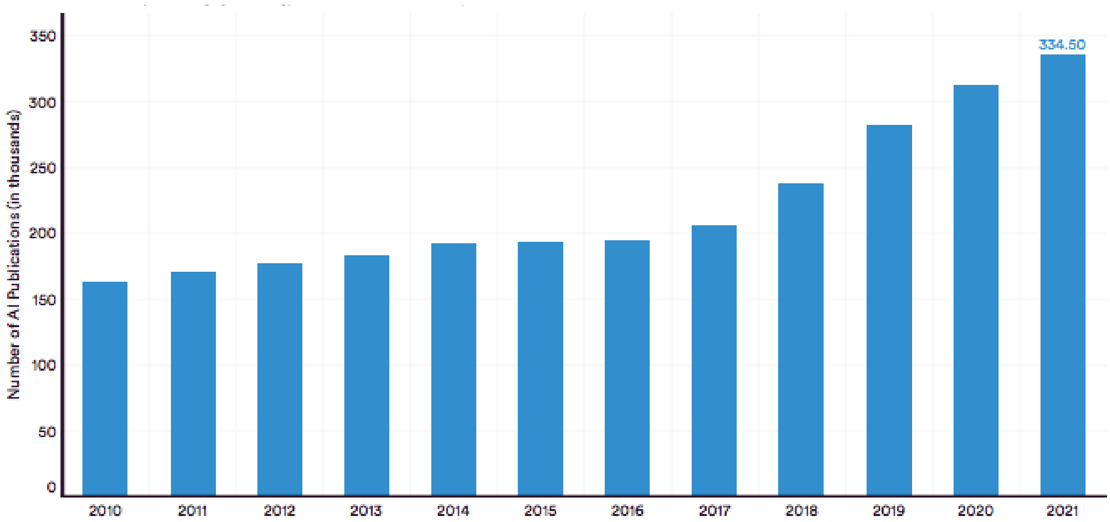


Figure 4: number of ai publication in the worlds, 2010- area, 2020-2021.

Source: center of Security and Emerging technology, 2021

As I was mentioning before, the main AI-developments driver are data, and in particular accessible and "good" data.

It is obvious that the actual records achieved by the AI industry have been reached also thanks a bigger availability of data, both from for the pure academic stand point as well as for the organizations one. This path, in particular, emphasizes the fact that bigger supply and presence of data let their costs decrease importantly. For example, according to the "AI Index 2022 Annual Report", the cost for training a prediction machine for the picture recognition decreased from 2018 to 2021 by 63,6%[8] .

[6] "Prediction Machines. The simple economics of artificial intelligence", by Agrawal, Gans and Goldfarb, Harvard Business review press, Boston, Massachusetts, 2018.
[7] "Prediction Machines. The simple economics of artificial intelligence", by Agrawal, Gans and Goldfarb, Harvard Business review press, Boston, Massachusetts, 2018.
[8] "The AI Index 2022 Annual Report," AI Index Steering Committee, Stanford Institute for Human-Centered AI, Stanford University.

Is the cost efficiency the unique improvement due to more data availability? Not at all. Another, very important aspect to be considered when we talk about new AI improvement is time. The fact that prediction machines are self-learning tools implies that, if they have more (and better) data, they have the chance to learn more and if they do so, they are able to find out a mistake in a quicker way, speeding up the overall process.
In fact, this aspect, in the Stanford University report, represents a pivotal change in the AI industry: the time for the machine training is reduced from 2018 by 94.4%.

Another important aspect that deserves attention is to frame in which industry the AI is mostly spread.
In particular, by looking at the governmental expenditure allocated to AI, it is easily found that AI has always been importantly used in the military industry and in the high-tech industry.
On the other hand, in more recent years AI has been widely used in other industries. On the chart below we can observe the US expenditure in AI divided by industry: it is easy to see that the expenditure in AI is widely favored across all the government departments, meaning across all industries of the country.

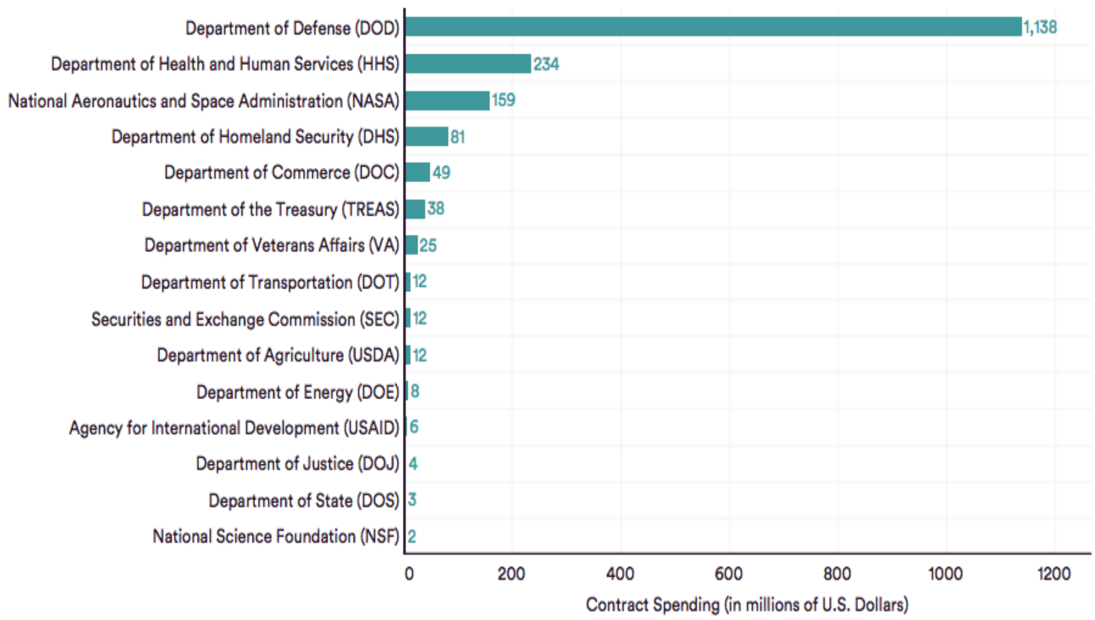


Figure 5: top contract spending on ai by U.S government department and agency, 2021.

Source: Bloomberg Government, 2021.

All the AI's hype in the market, of course, attracted the attention of regulatory bodies and legal experts: several stakeholders get started to meditate on the possible implications, both from an ethical stand point as well as a pure legal one that prediction machine can have on people and, implicitly, on the world economy. Indeed, the AI is now present basically in all industries (with different weight) and it can importantly be leveraged on different aspect of the business, across all the value chain.

A part of the economic side of the issue, another angle of the legal concern is about the privacy breach: the difference in countries legal systems is creating a polarization of big data producers and purchaser, like Europe.

Getting inspiration from David Ricardo, countries that are enjoying an absolute advantage, due to flexible legal environment, are able to export data (like China) while, on the other hand, who suffer it (some EU countries in particular) will buy them (or better still, some of them).

So, the increasing exchange and deployment of data across countries implied a dramatic increase of disputes and, at the same time, of government law proposals.

Across 25 countries taken into consideration, the "AI Index 2022 Annual Report" showed that the new AI-related proposal of law increased from 1 in 2016 to a peak of 18 in 2021. The leaders in the global market are, of course USA, followed by UK and Spain.

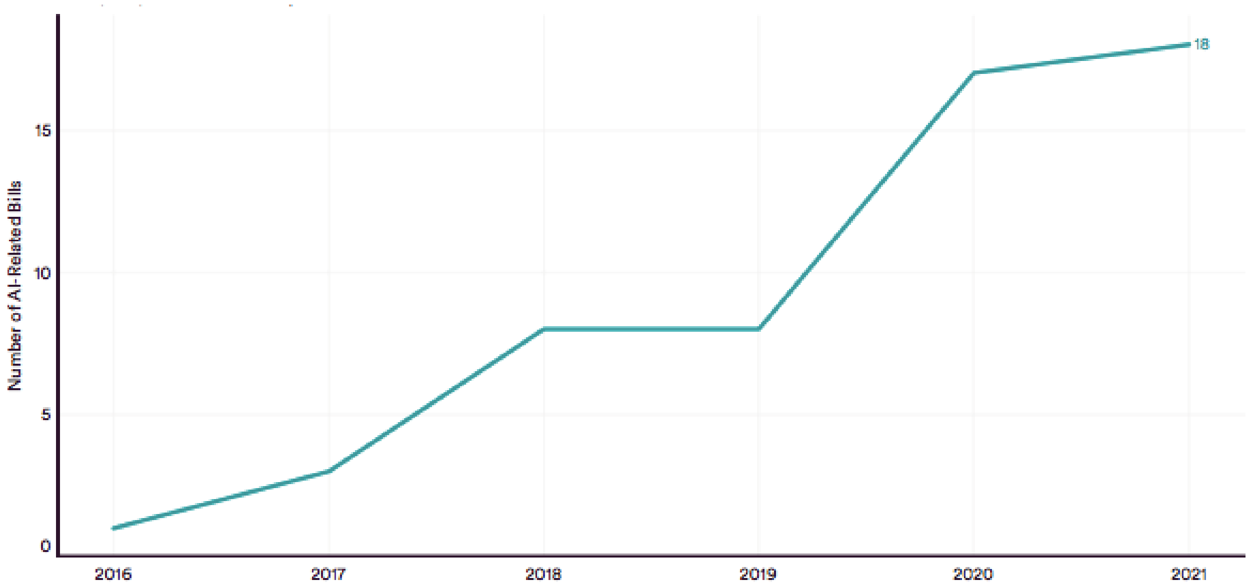


Figure 6: number of ai-related bills passed into law in 25 selected countries, 2016-2021

Source: AI index, 2021.

1.4 Artificial intelligence and pricing

The usage of artificial intelligence and its wide scalability across the industries and different companies' size, in recent years, arose the attention of regulatory bodies, government, policy makers and, of course, antitrust institutions.

The focus of this market agents is particularly strong in situations in which AI come into action in price setting strategies. This happens when the algorithms are used in understanding which could be an optimal price given some market conditions (cyclicity, festivities, consumer willingness to purchase and others). This, not surprisingly, has important impact on market composition and competitive structure, thus policy maker concerns.

The issues concerning market composition and price setting mechanisms, especially when prices are sustained in a supra-competitive way, have been studied since many years. In fact, in particular before 1980s, the main focus of antitrust institutions was on the formation of irregular/illegal market composition (S. Assad et al, 2021). In particular, the aim was to find policies to drastically tackle and reduce market conditions in which few players were reducing the competition by committing one each other (through legal/illegal incentives and punishments). Collusive behaviors would usually regard prices, sales condition, levels of production and distribution channels.

Interestingly enough, this phenomenon is recently boosted due to the fact that the cost for adopting AI solution for pricing mechanisms is importantly decreasing, thanks to the large supply of algorithms.

A part from illegal monopolies, well known examples of this market configuration are cartels, also known as trust. This market configuration, that already in the 18th century characterized the coal and train industries, is still attracting the concern of policy maker that, with the tools at their disposal and across different jurisdiction paradigms, try to find innovative way to detect, punish and dissolve cartels. The reason why there is so much attention on this phenomenon is due to the fact that high prices and limited number of participants can increase profit, at the expense of consumers surplus and induce inefficient market outcomes.

More recently, even if the issue concerning the trust and the monopolistic market configurations still exist (and will last), there is an increasing attention on the effect of deployment of algorithms on prices and "implicit" collusion behaviors that do not require an explicit agreement among participants. In particular, according to Stephanie Assad et al. (2021), from the '80s, algorithms have heavily been present in industry like airlines, hotels and financial markets (S. Assad et al, 2021): pricing and trading decisions were the first strategical area that relies on AI system for decision making processes and CRM (consumer relationship management).

Nowadays, thanks to technological improvements and better algorithms, a new class of AI systems is now available. The space deserved to them importantly rose and the accuracy of these machines is now reaching incredible level, never reached before.
In fact, the biggest majority of the e-commerce platform are now using AI as guidance tool for pricing and, according to the scholars such us E. Calvano, S. Assad, A Ittoo and R. Bawack, it seems to create consistent positive impact for company profitability but still a subsequent decrease in consumer surplus.
In the remaining part of this second chapter, I will review the literature dedicated to this topic by looking at which technology enables firms to collude and to the different market factors that may or may not contribute to sustain certain prices

1.5 Artificial intelligence and e-commerce

The way by which consumers are purchasing and the way they are keeping contact with firms is importantly changing, especially in the last two decades. The e-commerce platforms are changing the rules of the game in purchasing habits and, in more recent years, also the way consumers get information and are guided to buy and sell online.
In 2021, the e-commerce in Europe worth more than 3,5 billion of euros and represents more than 20% of the retail sales. This number are still increasing and have been importantly boost due to the covid-19 pandemic: the chance to purchase from home represented, in the 2020-2022 dramatic period, a way to keep sales activity alive and to further convince the consumption through e-commerce for later adopters (more then 80% of the European population is now able and willing to purchase online).
As obvious subsequence, in the last 15 years, the literature and the research assets available on the topic of AI and e-commerce, importantly increased.
According to R. Bawack et al. (2022), the number of dedicated articles on AI and its different usage on the e-commerce, in 2022, reached more than 4000 articles.
The majority of these scholars' effort emphasizes the role of the prediction machine on several aspects of the AI, in particular for the online sales activities.

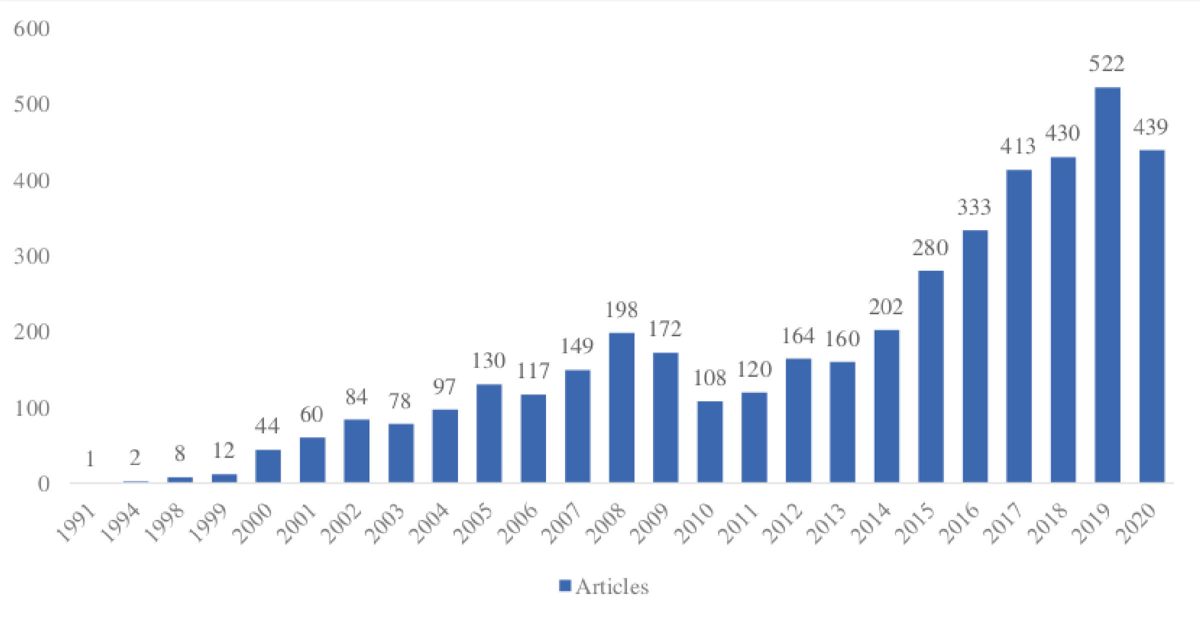


Figure 7: number of publications on ai in e-commerce per year, 1991-2020.

Source: "Artificial intelligence in E-Commerce: a bibliometric study and literature review", by Ransome Epie Bawack et al.

The weight that has been given to this topic, also looking at the pool of papers and articles, suggests the importance of the artificial intelligence on the price design activity and on all the opportunities that this technology is giving to both firms and consumers.

In this sense, according to Gartner (2021) 80% of the e-commerce interaction have been mediated by AI systems (like through bot and chat-bot)[9]. In addition, AI enhances the e-commerce conversion rate on purchasing activity by 915% in the last decade and the average online expenditure of customers by 3%.[10]

This has been possible due to the fact that, the deployment of AI in this context has been importantly spread across all the firm's value chain: from demand prediction, recommendation systems and price personalization to the entire distribution chain.

In fact, the role of prediction machines is not only focused the demand side.

By analyzing the company overall value chain and the "profit pools", it is noticeable that the footprint of AI is present everywhere, also in the supply chain side.

Therefore, this is something that is currently, of course, interesting for entrepreneurs in all industries: if there is the chance to frame and forecast with small error the demand and to personalize the offer by a certain price range, eventually for a certain geographical area (for

[9] https://www.actualidadecommerce.com/it/inteligencia-artificial-ia-en-el-comercio-electronico/
[10] https://www.actualidadecommerce.com/it/inteligencia-artificial-ia-en-el-comercio-electronico/

instance), then it is crucial that a firm has strong capability to manage the warehouse and the supply chain to capture the full value.
For this reason, the prediction machines, when properly set, can in fact importantly help in bridging the gap that it may exist between the consumers' needs (demand) and the most efficient way to satisfy them (the price and the distribution). This is also why one of the biggest beneficiaries of the deployment of AI technology is definitely the e-commerce: it reduces the human error and, for some extent, can detect market opportunities that otherwise would be lost. In particular, from a pure market-oriented stand point, the prediction features of AI help companies and entrepreneurs to capture a full value from the e-commerce platforms thanks to the fact the it can increase the customer purchasing convenience. In particular, if there is the chance to forecast and predict demand (with an increasing accuracy), then it is obvious that there is the chance to personalize prices along the demand curve and enhance the consumer satisfaction, leading to a higher competitiveness and profit maximization.
The price, still today, given the important polarization of wealth distribution worldwide and the market composition, plays a pivotal role in companies' strategy.
In this sense, AI is not only helping in understanding which price firms will opt for but it is also impacting the way companies act one each other, their competition, their cooperation and thus their business model.
The aim of this literature review is to tackle this issue, understanding and summarizing which are the relevant point of view and the different perspective that are now interesting the main scholars and the most important reference on this topic.
More in detail, there are two mains stand point that are importantly different one each other.
A first one suggests that AI is deployed on price setting mechanisms, in particular on the e-commerce, to help companies to sustain high prices, meaning prices that are set above the company's marginal cost. This means that this companies are able to make positive profit, even competing one each other.
On the other side, the second pillar of discussion is opposite in comparison with the first one: in fact, following several scholars, the usage of AI in companies can affect the firms' prices letting them decrease up to their marginal cost.
The two stand point are opposite but, in any case, importantly supported by a quite wide literature and are still evolving due to the rapid change of regulatory bodies and new AI systems. At the same time, it is also noticeable that the two different way of looking at the problem, can, for some extent, have some meeting points for what concern the market configuration, the information accessibility and, of course, the different regulatory environment across different countries.

1.6 Q-learning

The latter class of AI-powered algorithms lies on the capability to learn from errors in order to achieve a particular goal, like price optimization.

For this reason, this kind of system can be defined as a reinforcement learning model.

More in detail, machine learning (ML) is a scientific field that studies new methods to improve algorithms' tasks. In fact, machine learning has been seen as part of the commonly called artificial intelligence.

Its functionality starts with the choice of a pool of data that, technically speaking, is called training data.

This starting pack of data is used for filling algorithms that will elaborate them and will restitute an outcome.

For the scope of this work, algorithms using machine learning methods will deliver prices as outcome.

In the following chart, there is a representation of a classical machine learning process.

Figure 8: the machine learning process

Source: analisidiborsa.altervista.com

The process, generally speaking, is divided in 5 different steps:

1. In step one machine learning scientist find the most correct source of data. In this first phase they need to purchase a relevant training dataset that fill be used to fill the algorithm afterwards.
2. In the subsequent step data scientist clean the data set they purchased by any source of bias for the model. In this phase it is crucial to know well the field of research and data scientist knowledge is still an essential factor. The second step is a phase that it is not always needed but that can boost the outcome accuracy.

3. The third phase is the one in which there is the selection of a machine learning model. Models can differ one from the for several factors but, generally speaking, each model follows the so called "Bellman equation". This equation enables the algorithms to predict future values based on immediate rewards they have for correct values' prediction and discounted future values.
4. The fourth phase is a step in which there is, after the algorithms' predictive activity, an analysis of the results obtained. This is an extremely important phase since it gives the chance to data scientist to seek for errors and improve the prediction machine accuracy.
5. In the last step of the machine learning process there the need to give a graphical representation of the results. This will give the chance to divulgate algorithms' outcomes to everyone and not just for data analysts.

The first time Q-learning machine was presented back in 1989 by C. Watkins.
More recently, after years of study and insights by scholars in the industry, Google Deepimind, a British AI subsidiary of Alphabet, released the most updated version of a Q-learning algorithm called "Deep learning" (also known as deep reinforcement learning").
The latter version of the latter AI-powered algorithm is able to run with much lower human intervention, in a dynamic environment and with an increasing accuracy arising from the learning curve that these machines can exploit during the time.

In fact, given a set of potential factors (for instance competitors price) and several observations (previous market prices and quantities), the algorithm discovers the best profit-maximization path according to a certain data-scientist design of the machine learning model.
This means that AI can be "instructed" to act in a certain way but taking into account human instruction on factors to be considered and algorithm's design.

In the following paragraphs, I will collect and propose several examples and models that will help in better frame this topic.
This will be possible thanks to several works released by some of the best scholars that dealt with this interesting topic.
In fact, by looking at the still premature[11] literature, I discovered two ways of seeing the impact that algorithms have on the pricing mechanism in e-commerce.

The first stream of the literature that I will address argues that the use of AI favors and facilitates collusion on a supra-competitive price.
The second, on contrary, explains that, due to AI, firms operate in a competitive environment, with online prices equal to their marginal costs.
I want to anticipate that, these two opposite still interesting ways to look at the fascinating topic are currently both taken into consideration not only by passionate, scholars and students but also by government and regulatory bodies.
This gives to this job a valuable resonance not only from an academic perspective, but I hope it could represent an interesting starting point to know more about the topic and deal with it in an updated way.

2. Artificial intelligence as supra-competitive price facilitator

2.1 Price as result of reward and punishment path

Artificial intelligence solutions for firms are, in the last twenty years, increasing exponentially. This is offering to entrepreneurs a new paradigm for managing firms, in particular in pricing decisions.

One of the main factors that supports such paradigm is the fact that Q-learning algorithms may help AI adopters to tailor prices also looking at the external environment: when it comes to set a price, it is not just about finding the meeting point between demand and supply, but it's also about understanding and take into consideration extrinsic factors and other players' actions.

Better still, it's mainly about to find the most appropriate way to let Q-learning algorithms be able to predict extrinsic features and thus a proper price.

Calvano et al. (2020), in the paper called *"Artificial Intelligence, Algorithmic Pricing, and Collusion"*, have a built, in absence of empirical evidences (as discussed before), an experiment to test how AI pricing agents could interact and choose prices in a market place.

The aim of his experiment is to demonstrate how market agents could collude on prices and to find any factors that may/may not contribute to sustain supra-competitive prices.

In order to do so, the model designed by the scholars is based on Q-learning algorithms.

They decided to focus on this kind of prediction machines for several reasons.

First of all, Q-learning algorithms are importantly used in real world situation. This allows this experiment to enjoy a technology that represents the closest one to real conditions.

Secondly, Q-learning-running machines are relatively simple and easy to be controlled. This gives to the authors the chance to better control for parameters of the algorithm and to detect any possible model improvements, in an intuitive and relatively easy way.

Third, these kind of prediction machines have been successful and, even if much simple than others, are nowadays obtaining very encouraging results in comparison with similar but more sophisticated algorithms.

The model by Calvano et al (2020) is based on Q-learning algorithms that compete one against the others. In particular, each algorithm interacts with the others in a Bertrand oligopoly fashion. This implies that algorithms can simultaneously and infinitely play in a repeated game basing their competition on prices.

More precisely, each algorithms' action is based on how each of the prediction machines acted in the past within the experiment.

For this reason, each of them will opt more frequently for actions that were successful and less for action that were not successful in the past.

In fact, the algorithms (which we can consider as players of the game) compete on prices one against the other according to a different punishments/rewards scheme.

More in practice, the different outcomes of each competition correct the code ("the guidance rules") the algorithm follows to compete, leading to a prediction improvement: if the two firms will collude, the algorithm enjoys a reward signal while, if they not collude on a certain price level, a punishment action is put in place to improve the prediction machine.

The chart below helps in understanding the conceptual flow behind the model and the relative machine learning functionality.

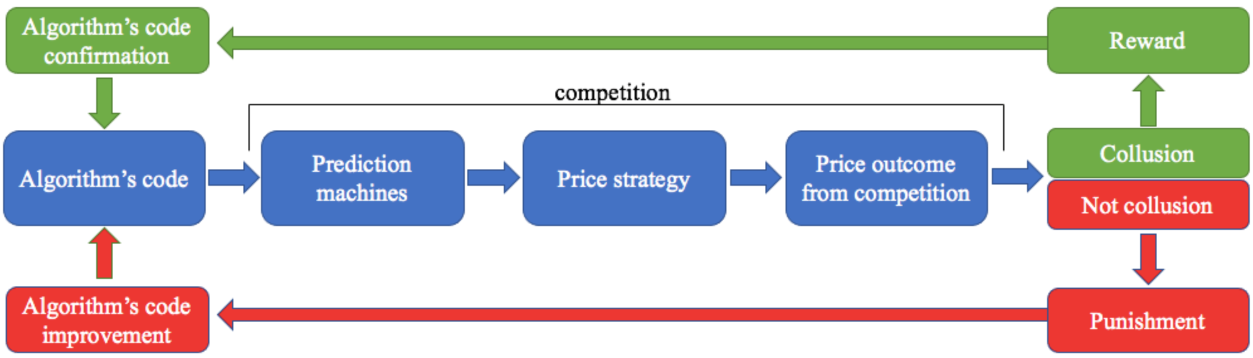


Figure 9: machine learning functionality and process flow

An important aspect of the model is the environment where the different algorithms interact.

The players in the experiment play in an artificial environment, meaning within a set of rules that are not realistic.

This is done on purpose, since this way of designing the model allows the scholar to keep track of their actions and to control for some variables.

In fact, the model has been thought in away such that the algorithms[12] can interact in 1000 different experimental sessions

[12] The number of algorithms is not explicitly expressed. Given the oligopoly setting we can assume the model is built on a bunch of players.

In particular, in each session, algorithms can play one against the other, opting for different prices setting strategies across different periods. This means that in each session there are several periods (we talk about thousands of periods in each session).

In each period, the algorithms will compete trying to maximize the profit basing their strategies on past performances and on improvements coming from the relative punishments/rewards path.

Each of the 1000 sessions will stop once the algorithms converge to a price, meaning when each player's pricing strategy is the same for at least 100.000 consecutive periods.

This means that after 100.000 periods, the learning process arising from the punishments/rewards scheme for each Q-learning machine is assumed to be ended up and the collusion in possible.

This implies that, looking at the Calvano et al. (2020) model, we can notice that the final price will then be the result of continuous strategies' adjustments based on the learning path across thousands of firms' interactions.

The aim of this experiment was to demonstrate how and if market agents could collude on prices by AI solutions and to find any factors that may/ may not contribute to sustain supra-competitive prices.

The main outcome the authors found out is that collusion is possible due to AI deployment.

In particular, this is possible thanks to a punishments/rewards scheme that allows the players (prediction machines) involved in the experiment to collude and, at the same time, in case of deviation, to enforce the punishment scheme.

In fact, the very innovative aspect of the model is the fact that they found out that AI can help firms in sustaining supra-competitive prices. This happens when punishments and rewards "educate" each of the algorithm to collude: when a firm defect from the price agreement, a punishment corrects the algorithm. This, thanks to a Q-learning technology, allows, during the time, to improve the algorithm accuracy, leading to collusive outcomes.

More particularly, the punishments' nature deployed in the experiment is the real reason why the collusion can be sustained: the punishment is finite in time, meaning that it lasts for a certain time (t). This enable the Q-learning machines to recognize the error, update the algorithm and let it gradually return to the price that was sustained before the deviation (Calvano et al., 2020).

Secondly, another relevant aspect to be considered is the punishments scheme.

The punishments scheme is absolutely the most important, and certainly interesting, part of the experiment run in their paper. This is due to the fact that it has proved to be the real "educational tool" of the algorithm that allows to formulate prices. It is characterized by a dynamic structure,

meaning that it can change across the different sessions and within each interaction period. In particular the punishments start after an initial price war between the players. Once the punishments start to correct the algorithms, the players are guided to a gradual return to the price they were sustaining before the defection.
Here below, I insert a graph taken from the paper.
It shows how the prices, after the initial price undercut by players, gradually come back to a collusive level due to the punishment the algorithms receive from the defection.

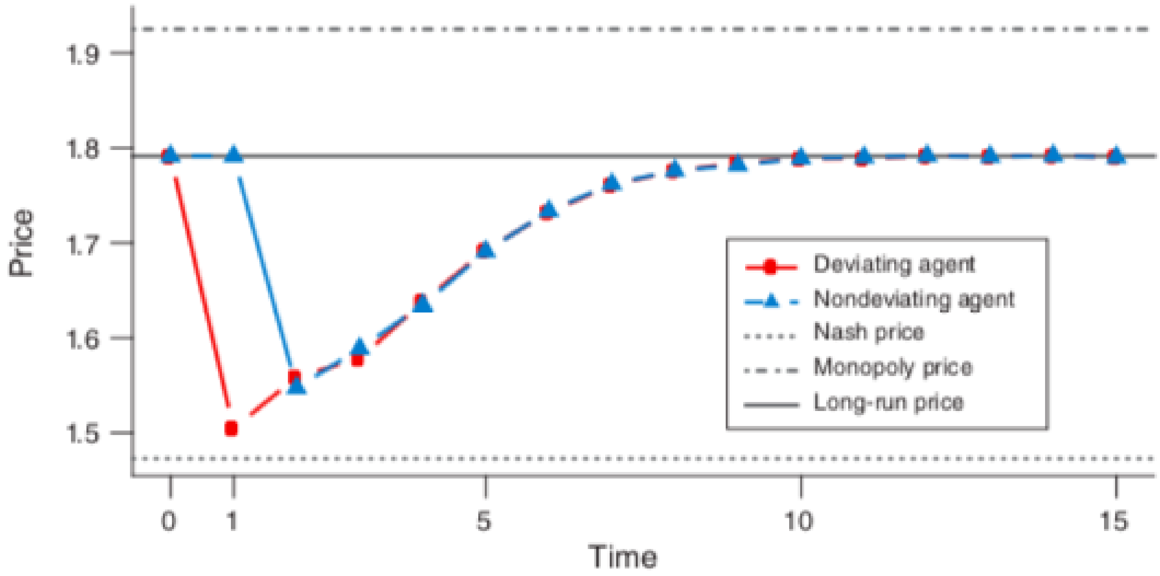


Figure 10: two firms' price behavior after defection

Source: "Artificial Intelligence, Algorithmic Pricing, and Collusion", 2020

Interestingly enough, this sequential scheme is sustained by the fact that, according to the authors' findings, 95% of the price defection let the deviation be unprofitable in comparison with the collusion.
More in detail, the punishment from which the algorithms learn is "stronger" and better perceived in the first sessions, that is when the defection (or price undercut) is particularly important and frequent.
In addition, it has been discovered that defecting players begin to memorize the effect of the punishment not immediately, but after 5-7 periods of each session. This suggests that the number of punishments is another key feature to be taken into consideration in this model.

Following the model, it is easy to discover that what makes the collusion really attractive is a proper mix of punishments and rewards. In fact, "*the harshness of the punishment is strongly correlated with the profit gain*".
The rewards and punishments path designed for the Q-learning machines, implicitly show that AI can help companies in sustaining high prices without a *"prior knowledge of the operating environment"* .
This is another important aspect of the model, since it implicitly assumes that the firms can learn how to operate and collude without have a given market experience.
This, also implies that all the players have the same starting knowledge of the market, enabling the scholar to equally evaluate their actions and giving robustness to the model.
For this reason, it is easy to understand that the players involved in the experiment have not been built or set up to directly collude.
Differently, they are designed to move prices according to the algorithm's guidance improvements. This means that, given a certain number of time and session into the experiment, they can learn how to collude, without explicitly interact with any other player.
A part of the algorithms' functionality (the rewards and the punishments paths), also extrinsic factor can contribute (or not) to sustain prices between the monopolistic and the Bertrand ones. To this extent, the model has some downsides that need to be considered.

First of all, the model is designed in an artificial environment. This is something that can affect the robustness of its results.
More in detail, the model, for example, do not take into consideration demand shocks, price increases, the probability of market downsizing, the industry differences (cyclicity, concentration), differences and updates in regulation and policies. All these phenomena, and many others, of course could affect prices and how firms compete, collude and so interpret price variations. This has important and unconsidered backlashes in the reward and punishment scheme and thus on the model under consideration.

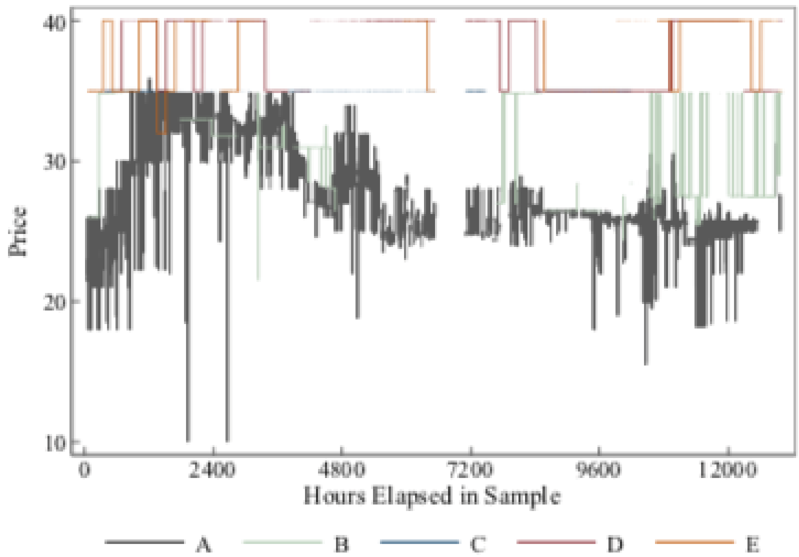
Secondly, the authors highlight that their model lacks in terms of algorithm control; this is particularly true for what extent the speed and the way each algorithm acts in the experiment.
So, even if the Q-learning machine are the simplest machines to control, still in turned out that there is difficulty in managing the complexity given by parameters changes and extrinsic factors effects.

This is something incredibly important, both theoretically and practically: have the possibility to completely control for the factors that can eventually *"destabilize collusion"* (Assad et al., 2021) can definitely lead to more consistent model's results.

In any case, the model provided by the authors is an extremely important work that has been considered by other scholars as a pivotal point for this topic.
In the subsequent part of this chapter, I will, in fact, continuously refer to this paper to show differences and specification made by other contributors.

2.2 How different price algorithms may impact on prices

The big demand of AI and algorithm-based solution, in recent years, increased the supply of such technologies around the world.
Currently, firms can choose between a wide range of different algorithms to compete and to run the daily activities, for instance the pricing ones.
In fact, particularly in the online market, the different technologies adopted can support (or not) market players in sustaining different prices, even for identical products.
Below, I insert a chart taken from the paper named "Competition in pricing algorithms" by Brown and MacKay (2021). It shows, by means of an example, the presence of different technologies' (that are A, B, C, D and E) for pricing during a testing period (0 to 120000 hours).



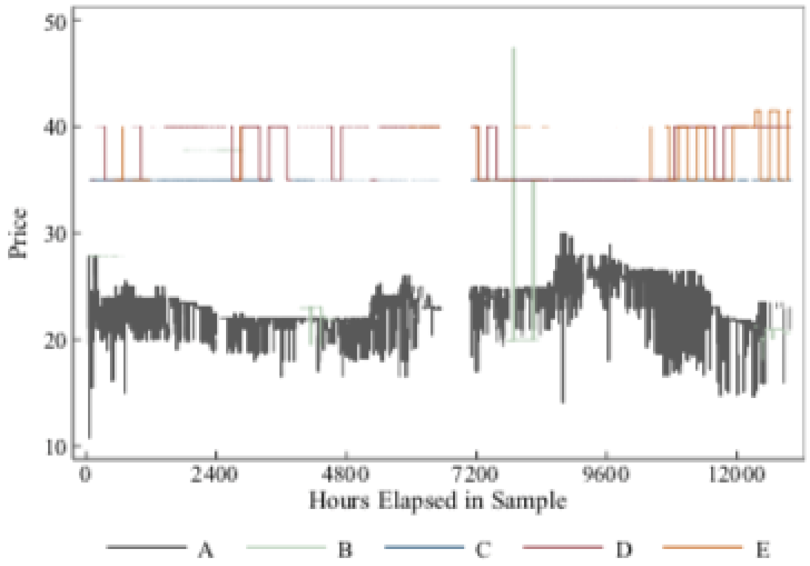


Figure 11: example time series of prices for identical products across retailers

Source: “COMPETITION IN PRICING ALGORITHMS”, 2021

As can be seen from the chart above, the differences among technologies could represent a factor that needed to be taken into consideration in pricing setting mechanism for firms.
This, in turns, given the increase in supply and the subsequent variety of algorithmic solutions, arose the attention of scholars that started to study the implication of such wave.
Among the others, the most important and recent work in this sense has been delivered by Brown and MacKay (2021), in which the authors study how AI contribute in online markets to change.

These authors compare two pricing algorithms that only differ for the frequency that they can adjust each-market-player’s prices: there is a first technology that can change the price with a higher frequency while, the other one, with a lower frequency rate.
For this reason, firms compete in a sequential way on prices and they react one against the other with two different velocity: there is a first firm which is faster in adjusting its prices to match demand condition and the competitor’s price changes and, a second one, that takes more time to do the same. They assume that each firm algorithm is a simple linear function of rivals’ prices. The two prediction machines compete in prices during a given period: firms can initially set their price according to the Q-learning algorithm at the beginning of each period under

experiment; then, depending on the technology they have, they will update their prices throughout the period.

The provided evidence is that firms with faster pricing technology quickly respond to price changes by slower rivals. This suggests that technological asymmetries could condition the pricing points of the two firms.

More in detail, they show that the firm that adopts the best technology (meaning the one the changes the price with a higher frequency), is able to sell the product at a 10% higher price (in comparison with a situation where firm do not adopt algorithms for pricing setting mechanisms). On the other hand, the firm that adopts a lower frequency pricing technology, is able to sell its product with a 30% price increase. Higher frequency algorithms, in fact, best respond to the lower frequency one by undercutting the rivals' prices. This, in turns, implies that the higher frequency firms, after several adjustments, will set a lower, still supra-competitive price.

The best technology (that is the one that changes the prices with a higher frequency) is able to generate higher profit in comparison with the player that adopts a slower pricing algorithm and to set a lower price and thus grab the whole market share for itself.

So, the choice of the technology and the velocity by which this act into the market, can be certainly considered an impactful, strategic and differential asset to be considered by firms.

In fact, the scholars stated that "*differences in pricing technology across firms leads to persistent differences in pricing for identical products*" (Brown and MacKay, 2021).

In real world condition, the technologies put in place for pricing strategies can embrace several paradigms and the firms involved in the competition can, for sure, be more than two.

In fact, in reality, firms can choose between a quite wide range of technology to adopt to compete in the market.

The chart below shows, in real world conditions, several algorithms' types and their differences in prices produced within a certain amount of time, for identical products.

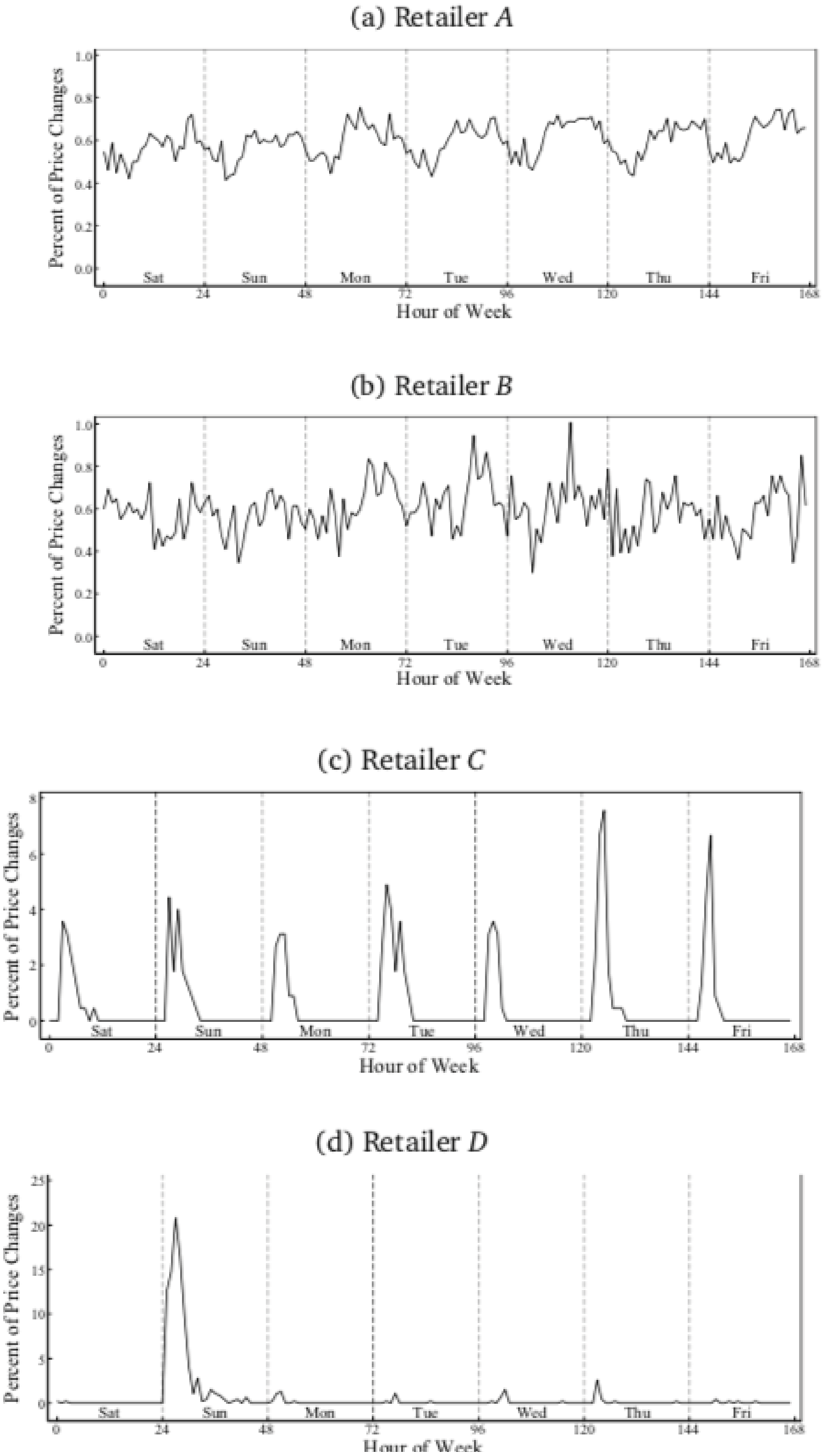


Figure 12: heterogeneity in pricing technology by one hour of the week

Source: “COMPETITION IN PRICING ALGORITHMS”, 2021

The last paper reviewed represents another relevant step ahead in specifying why firms can sustain collusive prices through artificial intelligence.

In particular, the latter scholars, even if with another "artificial" environment, added real world features to the previously seen models.

In detail, the latter paper highlighted the presence of different technologies and their subsequent impact on adopters' price setting mechanisms.

At the same time, taking into consideration the model's design, it turned out that the way firms compete in the model differ from the ones seen so far: the model provided by Calvano et al. (2021), is are based on a model in which firms compete a la Bertrand trough algorithms, while the model provided by Brown and MacKay (2021) assumes that firms, due to different frequency interactions, interact and compete in a sequential way.

These differences among the models let their comparison hard to be made.

2.3 Artificial intelligence impact in the monopoly market setting

Another last crucial aspect that deserves attention in this chapter is the impact AI has on a different market players numerosity.

All the model reviewed so far are based on very small oligopoly (three/four firms) or on duopolistic market composition.

For this reason, it is interesting, in this phase, to discover how the algorithms for price setting mechanisms can affect monopolists.

On contrary on what I previously described, in the case of a monopoly, there is no need to collude and to find an equilibrium price among the different market players.

However, a monopolist can opt for AI for others, still relevant, reasons.

In particular, Gans, in April 2022, delivered an interesting work named "AI ADOPTION IN A MONOPOLY MARKET": in this article he describes why monopolists could opt for artificial intelligence to set their prices, even if not affected by competition.

As we all know, monopolist for its nature sets, directly or indirectly, its prices above the marginal cost.

At the same time, even if lonely in the market, when setting the its price, it can be anyway affected by demand uncertainty.

In fact, looking at todays' economic environment, the scholar states that *"the price and the quantity choices of a firm become challenging and do not collapse into a single dimension"* (Gans, 2022).

The authors, to demonstrate his intuition, has built a simple model that is based on different demand curves and relative prices and quantities.

The author builds a simple model based on a comparative study: he designed an experiment in which he put in comparison two monopolists with different levels of market information.
The aim of the model is to demonstrate how AI deployment can affect monopolists' pricing points according to different market conditions.

Starting from the first firm, as showed in the graph below, it can enjoy full market information. This allows the monopolist to set the price knowing the demand composition and the relative prices and quantities.

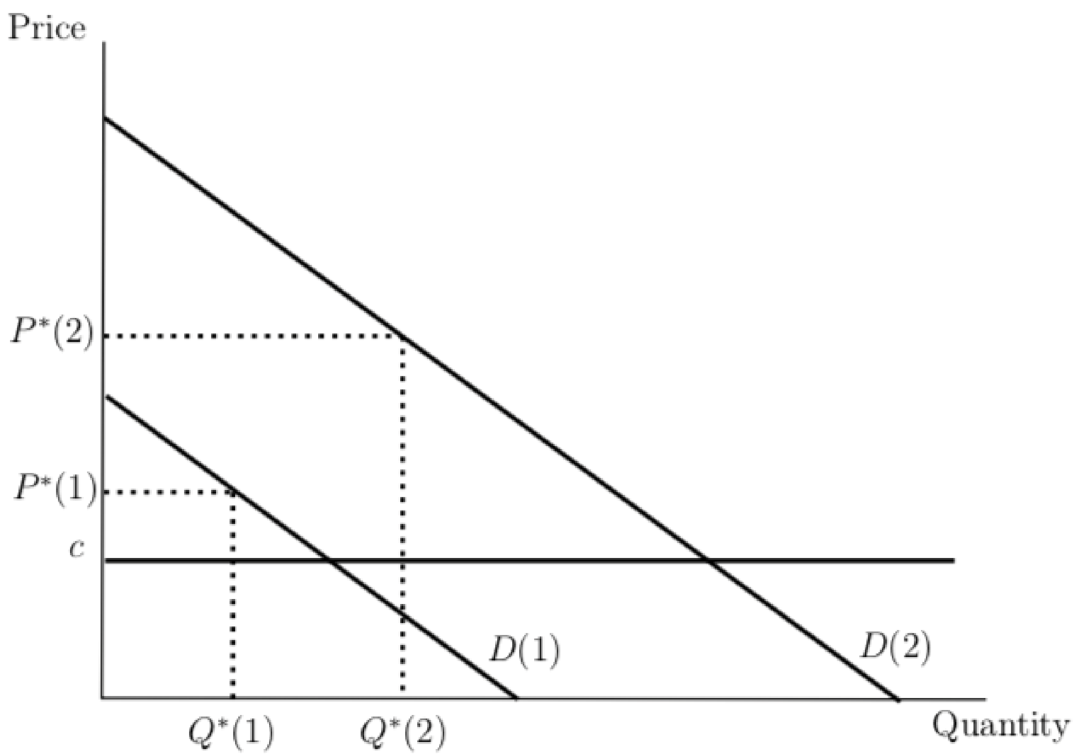


Figure 13: price and quantity under certainty

Source: "AI ADOPTION IN A MONOPOLY MARKET", 2022

In fact, given such conditions, the two demand curves, D(1) and D(2), are perfectly predicted. This implies that AI solutions for pricing are not needed. For this reason, in this first model, there is no presence of algorithms.

The second monopolist, on contrary, is immersed in a realistic context, where there is the presence of demand and industry uncertainty.

In the graph below, there is a graphical representation of the second model where risks, unknow factors and other uncertainty conditions affect prices.

So, in this case, the author assumes algorithms presence and their deployment by the monopolist.

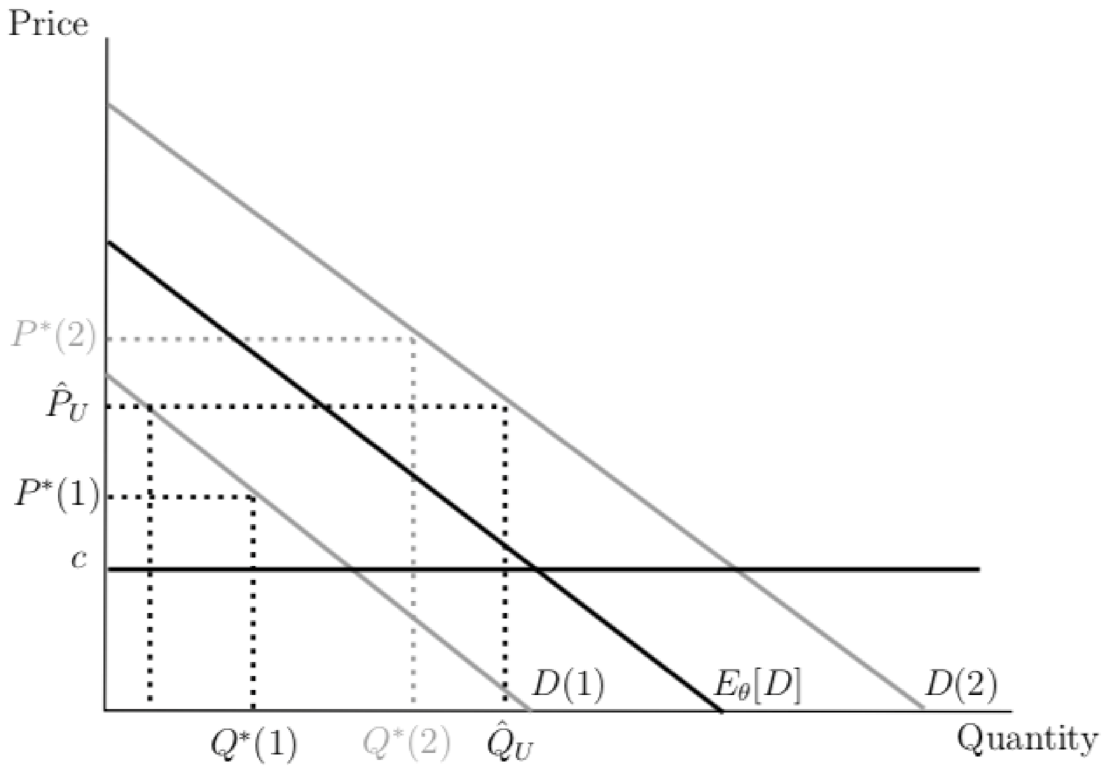


Figure 14: price and quantity under certainty and under uncertainty

Source: “AI ADOPTION IN A MONOPOLY MARKET”, 2022

In this second model, in fact, we can observe three demand curves, instead of two: the first (D1) and the third (D2) are the demand curves that are calculated as for the first model.

On contrary, the demand curve in the middle, E(D), is the one predicted by using of a prediction machine working under uncertainty.

The two models’ outcomes are, of course, very different.

In the first example, the information accessibility allows the monopolist to safely estimate the maximizing price and quantity for any demand shape: respectively P(1) for D(1) and P(2) for D(2).
This is given by the fact that, when there is full market information, the monopolist can autonomously predict demand conditions and relative pricing points, even without AI support. Unfortunately, as it is easy to understand, this is something that, in real world conditions, it can hardly happen.

In this sense, the author, in the second model, contextualizes the monopolist behavior in real world condition: uncertainty and lack of industry information play a crucial role in this case. In fact, artificial intelligence solutions have to deal with it for setting the price.
The authors, in order to show the differences between the two models, takes into consideration three demand curves.
The demand curves D(1) and D(2) are the demand curves estimated as for model 1, that is without algorithms.
This implies that, in this case, P(1) and P(2) are mere estimation of prices but under uncertainty conditions.
On the other hand, E(D) represents the demand predicted by the deployment of an algorithm in the same market (uncertain) condition. In fact, "Pu" is then the price predicted by the machine learning for the demand E(D).

The main outcome of the model is that when market conditions change, also the way we look at pricing estimation for monopolists needs to change accordingly.
In fact, according to the author, in an uncertain environment, the most accurate estimation of a price is given by an algorithm prediction: according to the second model design, D2 and D1 represent two demand curves' estimation that can over/under estimate real demand condition.
This implies that the monopolist that doesn't adopt AI in uncertain market conditions risks to not satisfy the demand and or eventually incur in increasing cost (due to inventory surplus).
So, we can state that the monopolist will definitely opt for AI pricing solution in uncertain environment since it will guarantee a still supra-competitive price and a better demand prediction.

It turned out that the improvement of demand forecast can definitely help monopolist to set their prices when information accessibility is hard to have.

This is due to the fact that we currently cannot predict 100% of the extrinsic factors that may affect the monopolists going concerns and the relative demand.
At the same time, what Gans (2022) confirms of the current literature is that, even for monopolists, AI can safely help in keeping supra-competitive prices thanks to better demand prediction.

What still remains abstract and to be studied among the scholars is how and how much we can currently control for uncertainty in demand prediction.
This is an open question and it is a factor with which all the scholars dealt with in an approximate way: both Calvano et al. (2021) and Gans (2022) explained their model designing artificial environments, making strong assumptions on markets conditions and their composition.
These decrease the reliability of this studies' results but encourage scholars and passionate to meditate to any new possible model that could better tackle this fascinating topic.

3. Artificial intelligence as competitive price facilitator

3.1 The impact of algorithm-based demand prediction on pricing strategies

A peculiar aspect of this topic is that, nonetheless the early-stage literature on the theme, there are already different stand points arising from the scholars and their important contributions. What has been seen so far in the review I propose is that better demand prediction can help firms to set and so collude on supra-competitive prices.
This implies that better algorithms (in particular Q-learning algorithms) can help companies in make higher profit but, consequently, to also decrease the consumers' welfare.

At the same time, a quite important pool of scholars, in recent years, started to see the effect of the algorithms' deployment for demand prediction from another perspective.
An increasing and consistent literature is, in fact, arguing that a better demand prediction can, on contrary of what seen so far, lead to a final price which is lower than the supra-competitive one.
This is an aspect which is exactly the opposite on what Calvano et al. investigated in their paper named "Artificial Intelligence, Algorithmic Pricing, and Collusion".
Among the firsts to study this new paradigm, Miklos-Thal and Tucker can definitely be considered as pioneers.
In fact, they are precursors, already from 2018, of the idea that algorithms can have a positive effect also to consumers, meaning that machine learning can operate setting lower price.

The model thought by the two scholars in the paper named "*Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers?"* is a classical and very intuitive one.
In fact, the two authors, to demonstrate their intuition, designed a model in which two firms compete on prices à la Bertrand.
So, to model is set on a duopoly market configuration in which firms, competing in prices, exchange perfect substitute goods and are united by an equal and constant marginal cost.

The main novelty they have made is that the two firms included in the experiment are equipped by algorithms: these have the same technologies, meaning that they can predict and forecast with a same and common accuracy.
So, what really makes their model peculiar is the study and the intuition they had on the quality of demand prediction for both firms.
As seen in the previous chapters, even if based on relatively "simple" model and in absence of empirical evidences, the authors have been able to discover new implications on different demand predictions.
So, rather than the model it-self, the main novelties delivered by the two authors is the way they look at the model and its implications.

In line with a big pool of authors, the idea behind the scholar's point of view is that better demand prediction could help companies in better customizing prices.
Their innovative outcome is that a better demand forecast increases the temptation firms have to deviate from collusive prices.
This happens because market agents, by using algorithms, can increase the way they frame the demand composition. This allows them to subsequently tailor their prices and so design a deviation from a collusive agreement.
More in detail, according to the authors, the temptation to defect from supra-competitive prices arises when firms have a technology that enable them to predict in a more accurate way the future demand (Miklos-Thal and Tucker, 2018). So, price undercut and prediction machine accuracy are strictly related variables.
Here below, to facilitate the reader, I summarize the logical flow behind their intuition.

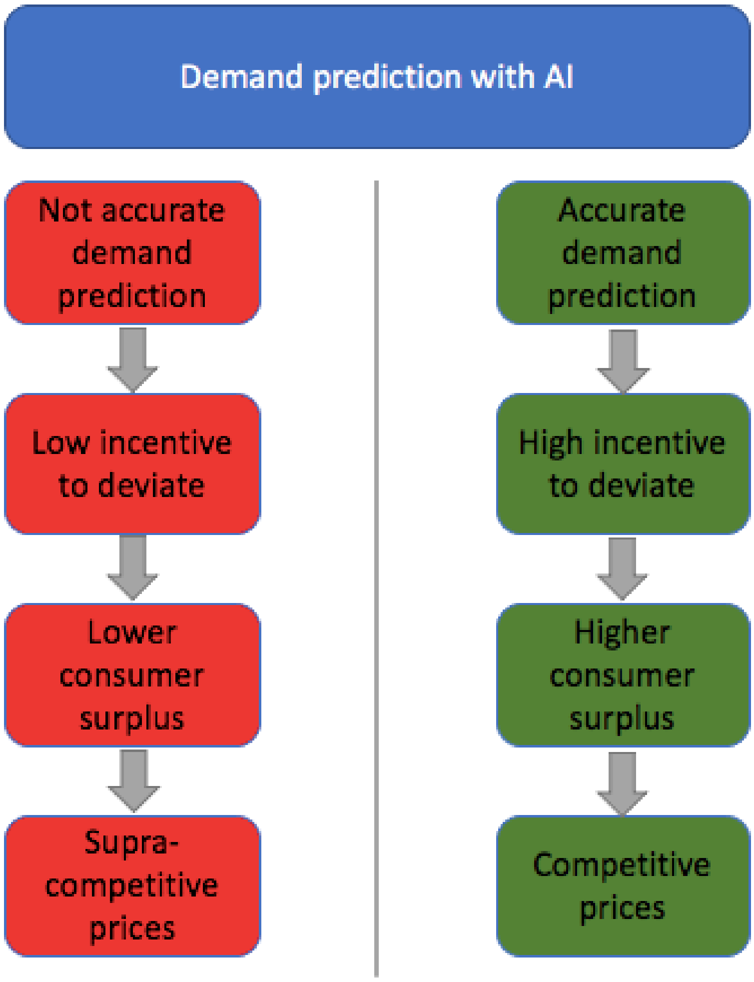


Figure 15: Miklos-Thal and Tucker's intuition framework

The chart basically explains the impact superior/inferior AI have on firms' prices and consumers' surplus.

Starting from a better prediction machines, what the scholars found out is that it enables companies to have a better forecasted demand.
This is translated in the possibility to properly set firms' prices and thus the incentive companies have to deviate from a supra-competitive prices' collusion.
Therefore, companies will undercut the prices, enhancing the consumer surplus and setting a final price which it is going to be a lower price in comparison with the collusive one (Miklos-Thal and Tucker, 2018).

On contrary, looking at the opposite side of the phenomenon, when algorithms for pricing are not accurate, the firms, given the uncertainty in framing the demand, will not be able to tailor their priced. In fact, according to the model, they will not undercut their prices and they will stick to a supra-competitive Bertrand collusion.
For this reason, consumers' surplus will then be damaged by this different situation.

So, when the algorithm enables firms to properly forecast the demand, the incentives to defect from the high prices increases and it should push the firm to respectively undercut until the profit equal to 0 (the price decrease reaches the firm marginal cost).
Interestingly enough, according to the latter model, in order to deter such profit-disruptive deviation, the market agents will then set a "below-the-monopoly" price (Miklos-Thal and Tucker, 2018) to keep positive profit.

The latter paper's outcomes have been also confirmed by O'Connor and Wilson (2020): in their paper named *"Reduced demand uncertainty and the sustainability of collusion: How AI could affect competition"*, they found out that when firms are able to predict industry shocks (like war, crises, new technologies and regulations), customers can benefit and can receive a higher surplus (O'Connor and Wilson, 2020).
In fact, what the majority of the scholars included in this literature review argued, is that, a part of the algorithms' accuracy, market information accessibility and market transparency are relevant variables to be considered.
In particular, the scholars agreed on the fact that better information and market transparency can lead to a lower level of cooperation.
This turned out to be an effect that can hurt the firms that are included in a possible collusive agreement but, on the other hand, can help in increasing consumers' surplus

Unfortunately, none of these scholars disclosed which is the final pricing point for firms and thus how it will be higher than the marginal cost.
However, looking at the available literature and the last reviewed paper, we can safely state that AI will lower the prices according to its accuracy and market condition but, again, we cannot precisely state how important this defection will be, both from consumers and firms' point of view.

These outcomes had also a big impact on the way regulatory bodies and governments look at machine-learning-based pricing strategies.
In fact, if it is true that the usage of AI for demand prediction increases the consumer welfare as showed by Miklos-Thal and Tucker (2018) and Sugaya and Wolitzky (2018), it is obvious that the current pessimistic point of view of regulatory bodies and policy makers on prices' on disturbing behavior have no basements (T. Sugaya and A. Wolitzky, 2018).
For this reason, according to the latter cited scholars, the big attention deserved on this topic could be, maybe, lower than the current one, or eventually focused on other aspects on the pending issue.

3.2 Players' communication through artificial intelligence and effect on prices

The idea behind the paradigm coined by previous authors represents an important common starting point for other scholars' works.
In fact, there is a wide pool of authors and scholar that argue that, given some particular conditions, pricing collusion is *"in general difficult to achieve"* (Schwalbe, 2018).
In this sense, there are several reasons that can justify such idea.
According to the next papers that will be taken under analysis, it seems that nowadays sentiment towards the AI collusive impact on prices is wrong and lacks of clear proof.
In the rest of this paragraph there will be the chance to understand why and how machine learning can drive firms to set competitive prices, enhancing the consumer surplus.
Among the others, a very particular and important advancement in this sense has been supported by Ulrich Schwalbe (2018): his point of view on this topic embraces the Miklos-Thal and Tucker's one but from a further perspective: the scholar has focused its studies more on the implications that communication between algorithms can have on final pricing outcomes.

In order to show his point of view, they did not build a new model from scratch.
On contrary, to demonstrate his vision on the topic, he preferred to opt for a critical review of the literature at disposal, adding relevant developments at the end.
The framework followed to support his innovative intuition is based on the following scheme.

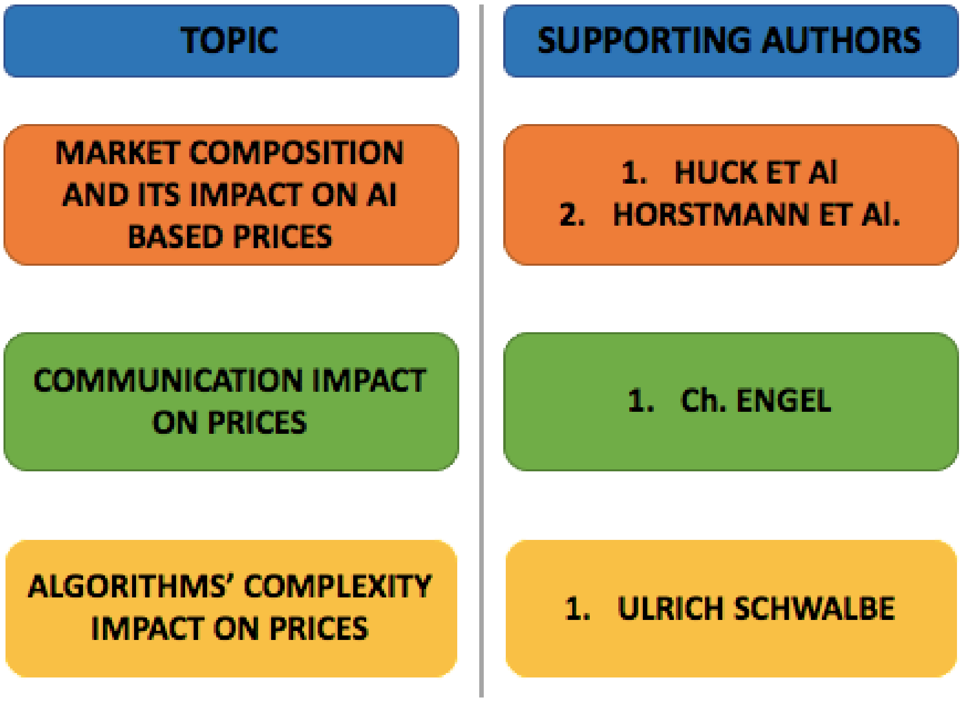


Figure 16: Ulrich Schwalbe's work structure

The structure of such work follows three principal blocks: the first one is focused on a general analysis of two works by Huck et al. (2004) and Horstmann et al. (2016) while, the second one is dedicated to deeper study on Engel (2015) and Harrington et al. (2016) papers.
The third last block is the authors advancement on the topic, where he adds important consideration related to the complexity of the algorithms and the relative impact on prices.

More in detail, the author's, within his paper named "*Algorithms, Machine Learning, and Collusion*", has found out that the pivotal point to collude (or to not collude) is the way firms communicate: this is particularly true when firms are more than two in the market (Schwalbe, 2018).
In fact, following his paper, it turns out that self-learning price-setting algorithms *"may learn to communicate but in a limited way"* (Schwalbe, 2018).
In particular, he stated that communication among market players depends on three main aspects: the industry/market specific settings, the communication path among algorithms and the complexity of the algorithms.

For what concerns the industry/market setting, we mean the market transparency, the number of firms, the level of competition, the level of regulation and all the other market features that characterizes a given industry and may affect the communicational flows among the market players.

In fact, when the environment where players operate is complex, an optimal pricing point become harder to be efficiently found out.

More in detail, the main feature that effect the industry setting, at least for a communicational stand point, is the number of firms in the market.

According to Huck et al. (2004), as far as firms in the market are two or three, there is still room for cooperation (collusion in prices) while, when they became more than three, it turns out to be extremely hard to cooperate (Huck et al., 2004).

This is something that has been definitely been confirmed and specified also by Horstmann et al. (2016).

These latter scholars argued that *"markets with two firms are significantly more prone to tacit collusion than market with three as well as four firms"* (Horstmann et al., 2016).

So, if we take into consideration a realistic framework where firm competing in a market are usually more than two, cooperation through AI seems to be difficult to be sustained.

This, according to Schwalbe (2018), will then lead to competitive price set by machine learnings and a subsequent increase of customers welfare.

So, according to this first part of the latter scholar's review, the number of firms importantly affect how they frame the correct pricing strategy to collude.

Then, the other important aspect considered is how firms communicate.

Again, even in this case, he tackled this point recalling others relevant authors' points of view.

First of all, the issue related with the communication between market agents have been pointed out already in 2015 by Engel.

In his paper named *"Tacit Collusion – The Neglected Experimental Evidence"*, he stated that when and if firms, even in an oligopoly, are able to communicate prices and quantities, "*collusion increase substantially and significantly*" (Engel, 2015).

This can be translated in the fact when market conditions (like players' numerosity) enable algorithms to properly communicate, the collusive prices can be sustained.

This has been studied and confirmed also by Harrington et al., just the next year, in 2016. They, in fact, specified that collusion could be possible only in a duopoly market setting if there is the chance that two firms' machines learning can communicate one with the other (Harrington et al., 2016).

A part of the industry setting and its impact on communication between market players, the third aspect taken into consideration by the author is the complexity of the algorithm.
With the algorithm's complexity we mean the (increasing) sophistication of the machine-learning and the other AI-related tools.
A machine learning that runs pricing prediction in unstable industries, with demand shock and strong important innovation turnovers, will be characterized by a more sophisticated algorithm: the variables to be taken into consideration are a lot and they change in hardly unpredictable way.
On the other hand, a machine learning that is put in place for pricing purpose in stable conditions, with no demand shocks and seasonal recurrent effects, will then be characterized by less sophisticated algorithms.
In fact, the more complex the algorithms are, the lower is the chance of coordination among market players.
For this reason, it is hard that AI solutions adopted by firms could lead to supra-competitive and collusive prices, especially when sophisticated machine-learning are used in environment with poor information accessibility and market transparency.
To conclude, according to Ulrich Schwalbe, *"given the current state of research in artificial intelligence and machine learning, the concern with respect to algorithm collusion do not seem to be justified at the moment"* (Schwalbe, 2018).

This last work is another example that shows how machine learning outcomes are affected by external factors.
In fact, nonetheless the important steps ahead did in terms of machine learning capabilities, the way firms communicate by algorithms remains an open topic.
This is due for two main reasons.
First of all, the current impossibility to fully understand the issue is given by the fact that, a part of the reasons described in this paragraph, the current stage of empirical evidences and practical examples seems to be very poor.
Secondly, the different firms that are, in reality, adopting artificial intelligence for pricing strategies are reluctant to share information. This is translated in the fact that learn how algorithms works and how they are prepared to act in different industry, remains unknow.

In fact, to conclude, Salcedo (2015) underlines that, to really understand how to let machine learning communicate one each other, there is still the need to understand how to decode the algorithms (Salcedo, 2015) and then to let them strategically set prices.

3.3 Learning-paradigms differences may influence price outcomes

The way how artificial intelligence algorithms (AIAs) works, depends also on how and how accurately they are able to learn from their activity.
This is the pivotal point of the Q-learning algorithms, the type of prediction machines used in all the studies seen so far.
More in detail, the question is how accurately the machine learning is able to learn from their mistakes and past actions as well as how good they can be in framing the environment (Asker et al., 2021) they work in.
This is very important since, based on these elements, the prediction machines will better design the best price and the different strategies to collude (or not do so).
In this sense, there are scholars that tried, focusing on different environmental design and different algorithms settings, to understand which are the main elements that may affect the algorithms learning curve and their accuracy.
Asker et al. (2021) focused their working paper named *"ARTIFICIAL INTELLIGENCE AND PRICING: THE IMPACT OF ALGORITHM DESIGN"* on the different learning paradigms and relative impact on pricing.

To show their point of view, the authors designed a new model, including into the analysis in just two firms.
The two market players compete on perfect substitute goods in a Bertrand fashion.
The novelty of this model is that the firms, quipped by artificial intelligence solutions, can use two different learning protocol in their competition.
More in detail, in the work they presented, they argue that when it comes to pricing, there are two different "protocols" that can be followed by the machine learning.
The protocols they talk about are: if algorithms' can learn from their action in a synchronous way or, on contrary, if firms that use AIAs learn in an asynchronous one.
The asynchronous learning happens when the Q-learning machines learn only from what they did in the past, and so from the pricing action they took before. T

his implies that this AIAs' machine learn exploiting mistakes and any rewords made/received in the past.

This, therefore, means that the algorithm's learning curve needs no information a part of the history of the past actions and profit gains: interestingly enough this paradigm also underlines there is no need to know about demand and market conditions, competitors' prices and the market rules (Asker et al., 2021).

The synchronous learning, instead, happens when the Q-learning machines *"conducts counterfactuals to learn about the return it would have learned had it taken an alternative action"* (Asker et al., 2021).

In this case, there is no need to learn from past action.

In fact, this protocol, to properly run and produce consistent prices (outcomes), needs to know about the underlying economic environment (Asker et al., 2021) and competitors' strategical actions.

Given the differences between Asynchronous and synchronous learning protocol, the three scholars decided to dept their study on the implication these have on pricing and on any relevant economic implications.

The first thing that has been highlighted is that, when the algorithm's weight deserved to future profit is low, the synchronous AIA produces outcomes that generates competitive prices, meaning prices below the supra-competitive one.

Differently, when asynchronous AIAs are put in place and the weight given to future profits is relevant, they tend to produce prices close to the monopolistic ones.

To give a practical evidence of the model's outcomes, below there is the chance to observe a graph taken from the last paper showing the different pricing outcomes looking at the different learning protocols.

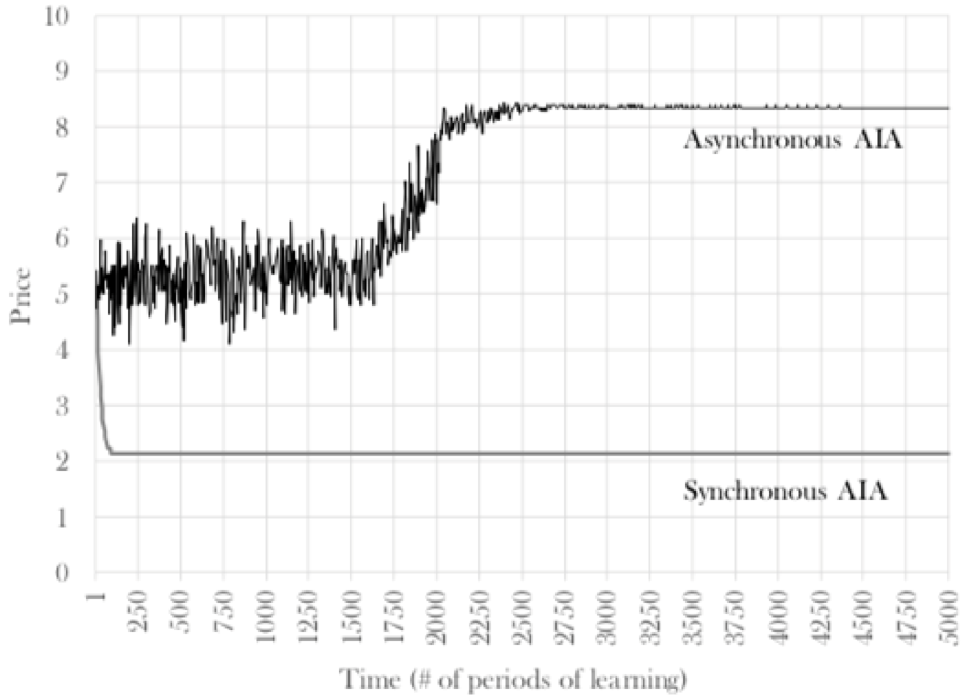


Figure 17: price path with different algorithm designs

Source: "ARTIFICIAL INTELLIGENCE AND PRICING: THE IMPACT OF ALGORITHM DESIGN", 2021

The outcomes are definitely clear: when the firms use a synchronous AIA for pricing, the final price is just slightly above 2, meaning that firms will stick to a competitive price that is just above the firms' marginal cost (Asker et al., 2021).
The figure below graphically focuses on which are the outcomes, during the time, when AIA runs in a synchronous way.

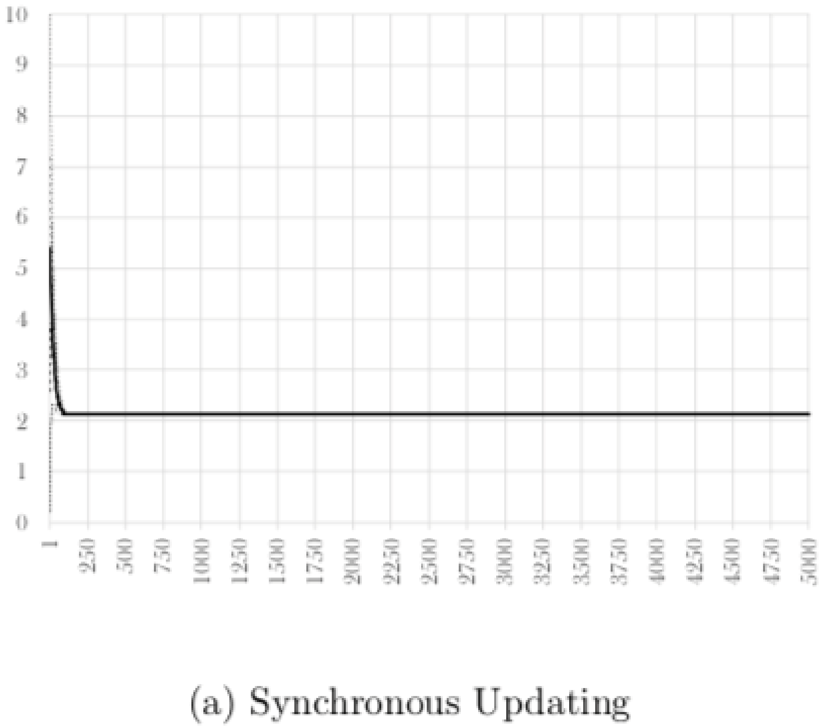


Figure 18: price outcome with different algorithms design - synchronous updating

Source: “ARTIFICIAL INTELLIGENCE AND PRICING: THE IMPACT OF ALGORITHM DESIGN”, 2021

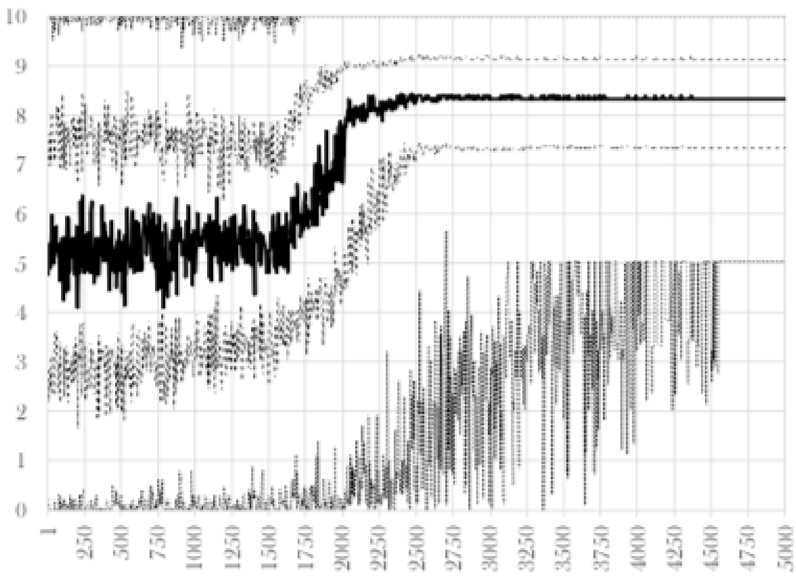
On contrary, when firms compete by deploying an asynchronous AIA protocols, they set the price close to the monopolistic one, that is 10 (Asker et al., 2021). In fact, in this case, the final price for the firms will be 8, instead of 2.

The idea behind such results is quite intuitive and depends on the way the algorithms are designed to learn.

In particular, when firms opt for an AIA that works in a synchronous way, the outcome from their interaction, during the time, “must be a Nash equilibrium” (Asker et al., 2021): every interaction are evaluated simultaneously for each time and they are evaluated in terms of the profit they generate.

Since the algorithms do not learn from past action but from the best alternative it would be able to produce, the outcome is the constant Nash equilibrium.

When the AIAs set by firms for competing on prices is asynchronous, they can update, based on past behaviors and actions their policy. This mean that they can update, give a certain frequency, their prices and then adjust them, reaching a supra-competitive one.
In the graph below it is possible to observe how, in the experiment run by Asker et al. (2021), several interactions among the firms can lead, due to an asynchronous learning protocols, to higher prices.



(b) Asynchronous Updating

Figure 19: price outcome with different algorithms design - asynchronous updating

Source: "ARTIFICIAL INTELLIGENCE AND PRICING: THE IMPACT OF ALGORITHM DESIGN", 2021

The working paper offered represents a very peculiar work for several reasons.

First of all, it confirms the thesis designed by Schwalbe (2018) on communication and interactions among firms.
More in detail, the latter paper makes a further step forward, analyzing the way machine learning can be affected by differences in communicating and why this can create different on adopters' prices.
At the same time, the three American scholars did not state if there is the predominant protocol and which ones we should take as the "commonly-used"; in particular, the working paper do not state which is the current situation on the usage/deployment of these protocols, which are the protocols mostly preferred by firms and which can, as consequence, be an eventual threat for competitions' law.
What stands out from their intuitive and descriptive working paper, is the fact that firms can choose between different protocols and thus arbitrary decide how to compete into the industry or market they live in.
This is something crucial from a legal/regulatory stand point since it can help in identifying, given some market condition and different pricing structure, the responsibility on breach of competition rules.
Another last important point that emerges from these working papers is the important confirmation that number of market players acting in a given industry affects the competition: it has been proved that, both in the case of synchronous as well as asynchronous learning process, the increase of firms into the market decrease the prices, leading to a competitive price setting (Chaim et al., 2021).

3.4 Different pricing outcome between algorithms' adopter and non-adopters

Another way to look at the price setting mechanism led by algorithms is to look at how firms introduce the AI tools in their production function and its consequent impact on prices, both in the short run as well as in the long one.

This aspect of the topic has been studied by several scholars led by Gans during the last two years: in particular, it surprisingly also turned out that firms that adopt algorithms for pricing setting mechanisms can, in some conditions, create a positive external effect also on non-adopter firms (Gans, 2022).

This means that both adopters and non-adopter's prices can be strongly affected by AI adoption. In fact, artificial intelligence, as form of innovation for firms, is quite peculiar and differ from the past form of innovation for several reasons.

Generally speaking, by looking at the economic history, especially starting from the steam engine invention, technological improvements have been adopted to let the companies be more efficient: the aim was to leverage on new technologies to lower the marginal costs and improve the available factors' productivity.

This, in turn, was seen a differential factor, meaning that the ones that adopted innovation within the company were able to be more efficient and make higher profit in comparison with the other market players (that were not able to deploy such new technologies).

Basically, new-technologies adopters were able to create negative external effects to the non-adopter ones (Gans, 2022).

This paradigm, according to author, it seems to be obsolete when the technologies in question are algorithms and, in general, artificial intelligence.

In his work "AI ADOPTION IN A COMPETITIVE MARKET, the scholar has focused on a canonical environment within which a continuum of firms, competing on prices, face uncertainty on demand.

The inspiration for his model came from an old observation that Richard Nelson did in 1961.

In particular, Nelson (1961) questioned himself on the impact demand uncertainty can have on firms' pricing behavior.

He suggested that firms' competitiveness and behavior in a competitive market importantly depends on the accuracy they are able to predict the demand composition.

Gans decided to build its model starting from this dated consideration but including in the uncertain factors also the effect that AI adopters can have on non-adopters' firms.
To structure his new point of view on this topic, the author built a two-period model in which a pool of firms competes on prices.
Each firm produces perfectly substitutable product with a constant and equal marginal cost.
The peculiar and new aspect of the model is that not all the firms taken into consideration can enjoys algorithm-based pricing mechanism: some firm swill set the price in accordance to a prediction machine suggestion while others, will set the price subsequently.
For this reason, firms will set the price in a sequential way.

The analysis of the model has been split in two parts.
This has been done in order to frame the firms' pricing behavior under uncertainty in the short run as well as in the long one.
In the first part, in fact, he deep dives in the behavior firms adopt for pricing in a short run period.
In the second part, instead, the scholar looks at the model in a long-run perspective, seeking for pricing differences vis-à-vis the short run framework.
This way of designing the model allowed him, as will be seen in the next session, to observe the different firms' attitudes in a way that has not been taken into consideration before.

The author argues that *"AI does not operate as a standard process of innovation and its adoption may confer positive externalities on non-adopting firms"* (Gans, 2022).
So, he basically states exactly the opposite of what has been seen so far in terms of new technologies' impact on firms: AI and algorithms can be useful for adopters and not adopters since it boosts companies' demand prediction capability.
More in detail, the first model's outcome is that AI creates positive effects for adopters since it ensures a higher flexibility in quantity and price adjustments. This is due to the fact that, as seen also from the other papers, algorithms can facilitate demand prediction.
For this reason, according to the findings in his work, it could be possible that, in short run, when adopters' price increases, non-adopter firms can enjoy a positive effect too.
This is due to the fact that non-adopter firms can observe adopters pricing strategies and tailor their own prices accordingly.
In addition, this phenomenon, in the short run, together with the increase of market agents that adopt AI, creates a spillover that can importantly mitigate the variance in prices' calculation.

This implies that the accuracy of pricing setting increases and non-adopters can also benefit for their pricing strategies as well.
For this reason, given the current increasing AI adoption trend, we can assume that, in short run environment, non-adopters can benefit from the augment of algorithms usage into the market they act (Gans, 2022).

Moving to the long run scenario, *"in the long run…market prices are, on average, lower and quantity is, on average, higher with AI adoption than without it"* (Gans, 2022).
In fact, in the long run, the "*availability and the adoption*" (Gans, 2022) of AI generates increasing outputs and a subsequent lower price.
This phenomenon is aligned with the other scholars seen so far: when firms, using algorithms, compete one against the other, generate outputs.
These outputs, from a machine-learning stand point, represent additional information that can be used for better frame how to set prices according to the other firms' actions.
For this reason, in the long run, following the Schwalbe's (2018) point of view, the enhancement of information accessibility will lead to lower prices.
In turn, as stated for the short run scenario, even firms that do not have algorithms-base price setting mechanism, they will observe adopters' prices and will accordingly set their prices lowering them.
This, then, implies that the final pricing point will no more be a supra-competitive one.

This model gives another perspective on this interesting topic.
In fact, the fact that the model has been designed to deal with two periods analysis, enable to discover novelties in comparison with the rest of the available literature review.
The fact that AI solutions can help firms in set prices that are competitive represents, from a consumer's welfare and regulatory stand point, a very important aspect to be considered.
At the same time, even if this paper is a great step ahead in the machine learning impact comprehension, it has some down side that needs to be expressed.

As it happens for the other papers in this literature review, also in the latter one there is the lack of practical example to justify what the scholar argues.
Again, the model is run in an artificial environment: this helps in properly frame another aspect of this topic but, at the same time, it does not give a concrete outcome proof of its validity in real world conditions.

In this specific case, another aspect that is missing, is the scalability of Gans (2022) model among the different industries.
This model hasn't the feature to be applied in different market contexts and across industry-specific settings: each industry has its own peculiarities and the effect of AI can impact in different way the firms accordingly.
For this reason, the model could be misleading and unprecise when directly applied in different contexts and market configurations.

Another element that deserves attention is the impossibility to compare this last model with the others in the literature review.
In fact, the model designed by the latter author follows a paradigm in which firms subsequently choose their prices while, the others presented in this literature review, are inherent to a model based on a simultaneous pricing choice.
In addition, none of the model seen so far analyzes the impact that algorithms have on prices decomposing the experiments in time periods.
In fact, it might be very insightful to have a comparison of the models not only based on outcomes and experimental design, but also on a time perspective as Gans (2022) did for the last one.
This reduces the chance to have a direct comparison with the other papers and thus a subsequent clear idea on the overall topic.
Again, this is a logical consequence of the emergent literature status and on the absence of practical evidences
For this reason, even in this case, there is the need to take the study outcomes as additional steps forward for this topic and as inspirational point for new academic improvements.

4. An alternative perspective

4.1 Possible price setting mechanisms resistance to artificial intelligence

What has been described so far represents a review of the literature closely related to the use of AI for companies' pricing mechanisms.
What has emerged is a fairly clear picture that has been, over the last ten years, consolidated with respect to two positions.
The first, as we have seen, argues that the pricing activity of companies through algorithms pushes different companies to compete with supra-competitive prices. This type of phenomenon has been extensively discussed in the available literature and it seems, looking at the media effect it is having, an idea increasingly taken into consideration.
The second point of view, on the contrary, seems to explain to us that due to the use of machine learning, companies are able to set their prices in a competitive way, just above their marginal cost.
In this sense, even if the literature seems to confirm it from different points of view, institutions and governments seem to be more cautious and carry tangible evidence, currently absent.

However, within the work, I considered it interesting to insert a new, interesting and still little considered research activity on an alternative point of view.
This idea stems from the fact that, although there is a clear division of the phenomenon into two parts, none of the authors has investigated whether and to what extent there is an effective impact of AI in pricing activities.
This particularly intrigued me because all the papers and models start from the idea that companies implement algorithms to for dynamic pricing.
Instead, I was interested in knowing if, in fact, there is an alternative evidence, outside the logic widely shared by the authors.

For this purpose, I went to broaden the search for authors and articles that could help me to have an alternative point of view, based on skepticism with respect to the effective functionality and the widespread presence of artificial intelligence in companies.
Indeed, looking at the numbers reported in the AI INDEX REPORT 2022, investment in AI for businesses has really increased.

However, this does not imply that all investments in machines learning in companies are aimed at pricing functions.
What emerges is in fact a strong propensity of companies to embrace the paradigm of artificial intelligence in a gradual way, starting from its implementation at an operational / industrial level and only afterwards in other functions.
This factor, less taken into consideration by the authors just seen, helps me to introduce a still little spread point of view.

A very small group of authors has begun to investigate what is, in reality, the actual use of artificial intelligence.
In this pool of scholars, the name of Claudio Piga stands out.
Together with others, he decided to investigate, through tangible examples, the real presence of artificial intelligence in pricing activities.
In general, this emergent point of view starts from skepticism about the pervasiveness, effectiveness and real consistency of the phenomenon.
The author, interviewed by myself, believes that at the moment, thinking that the use of artificial intelligence is widespread in pricing is very little justified.
That is, Piga (2017) believes that this is a theme inflated by the media, by a certain academy that loves and follows fashions, but which does not look at data in their actual description of a generalized phenomenon.
More practically, does it make sense to think that "since Amazon does it", the whole world does the same and we are even sure that Amazon does it?
This question, as seen so far, is very difficult to answer given the scarcity of tangible elements but the institutions are still absolutely attentive to it.
However, this is precisely the added value of this current of thought, namely the fact that there are certain, truthful and tangible evidence on the absence of artificial intelligence in price setting activities.
To better explain this issue, in the remaining part of the chapter, I present a paper in which there is a proof of what Piga and other colleagues have been arguing since 2017.

4.2 Empirical evidences on the absence of artificial intelligence for price setting mechanisms

Online travel agents, also called OTAs, are today a very important channel for hotels and restaurants.
Their function lies in being intermediaries between the company and the consumers.
This implies that these platforms could also be responsible for their online price visibility and positioning.
In particular, hotels subscribing themself on OTAs services have the chance to increase their visibility due to the fact that these platforms act as intermediaries between the industry of reference and the demand.
For this reason, these new kind of travel agencies are nowadays overcrowded by hotels, B&B and other hospitality-related firms that looks for platforms' visitors.
In fact, it is from years that hotels, restaurant and other structures are important leveraging on OTAs to increase their sales.

Unfortunately, as already highlighted for other models, very little is known about how and if these platforms manage pricing mechanisms.
However, authors have anyway decided to leverage on these platforms because they ensure the possibility to find large sample of hotels and to use them as tool to observe their (eventual) price changes.

The goal of their study is to understand if the pricing activities displayed on these platforms are driven by AI, meaning that prices automatically change according to markets settings (Dolnicar and Ring, 2014) or, on contrary, if they rely on uniform pricing, demonstrating the absence of algorithms in pricing.

The scholars built a simple model based on a probabilistic study to statistically verify whether there is presence on online travel agents of prices that frequently change (so dynamic prices) in accordance with demand changes or not.
In this sense, they focused on a large sample of hotels: the latter, to facilitate the study, have been divided into 5 groups, each of them characterized by quality of the hotel expressed in number of stars (1,2,3,4,5 stars), in a certain area.

This allowed the authors to divide the sample by hotels' quality expressed in "stars" and to statistically investigate what is the probability, in different time periods, of observing frequent price variation on OTA's websites when quality of the hotel changes.

This framework gives the chance to the authors to control for:

- Hotels' prices change by changing the Hotels' quality across different segments taken into consideration in each period of analysis.
- Hotel's price changes according to demand changes recorded on the OTAs platform in each period of analysis.

In addition, to give stronger validity to the model, they repeated the same empirical analysis in two consecutive years (2014-2015) in the same periods of the year.
This allowed them to reduce the uncertainty factors associated with a one-year analysis (like specific trends or waves).

The model clearly highlighted and defined that the propensity to deploy AI for pricing setting "is not as widespread as often the literature implies "(Piga and Melis, 2022).
In fact, the authors argue that there is no material evidence that most hotels are constantly subject to rescheduling of their prices in accordance with demand.
More in detail, it turned out that higher quality hotels (meaning 4 and 5 stars hotels) are more active in price changes than lower quality ones (1,2 and 3 stars' hotels).
In fact, the graph below shows the estimated probability of a price change over any day in one of the booking-period taken under consideration.

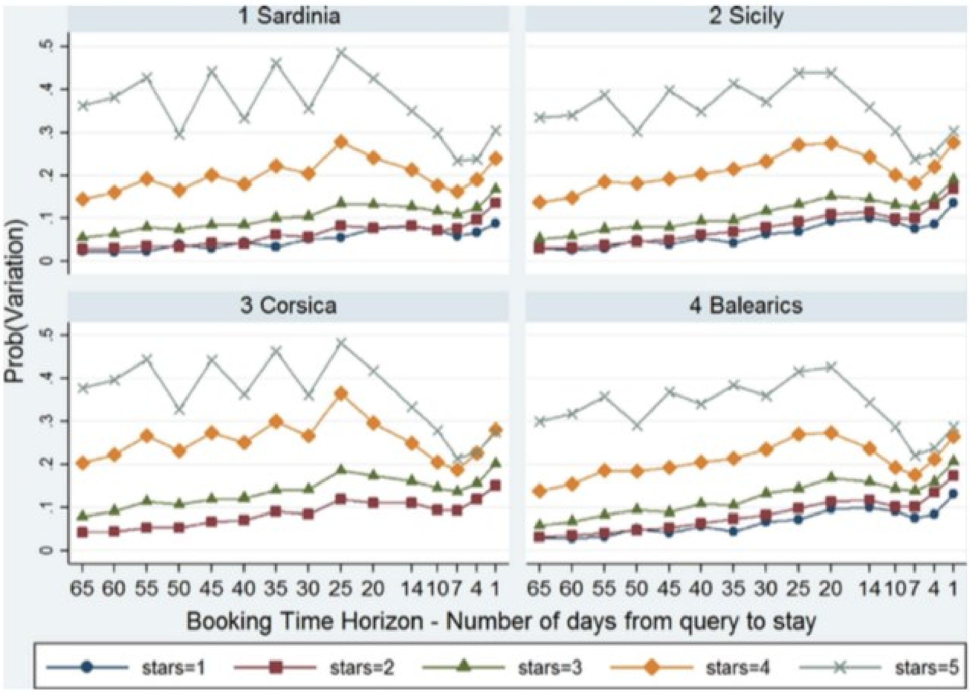


Figure 20: estimated probability of observing, for each day of stay, at least a price variation over the booking period – by star classification.

Source: "Are all online hotel prices created dynamic? An empirical assessment" 2022

Looking at the FIGURE 20, it is clear that, taking as variable the stars' classification, high quality hotels (such as 4 and 5 stars hotels) tend to have a greater propensity to change prices: this effect is particularly material for 5 stars hotels and less for 4 stars ones.

This, according to the authors, could be due to two different phenomena.

The first is the fact that the more premium hospitality companies are more structured than the lower-level ones. For this reason, they might have higher information accessibility and better managerial competences to set prices.

The second is that these price changes could be the result of an algorithmic activity that, matching the demand, tailor the price accordingly.

In this sense, there is no evidence that these price changes are strictly related with the presence of artificial intelligence solution or if the solely depends on managerial capabilities and more structured firms.

Conversely, lower quality hospitality companies seem to experience a lower variation of their prices. This, according to the authors, is just be due to the fact that these structures have lower

managerial capacity and higher aversion to risk in setting a price that can let the firm less competitive.
In fact, what favors a traditional pricing system is the implicit cost of the risk to antagonize customers for the price gaps they might incur vis-à-vis the competitors (Sahut et al., 2016; Viglia et al., 2016). This could be one of the reasons why lower-level hotels opt for less price changes.
So, the majority of the hotels under analysis, that is 1,2 and 3 stars structures, definitely do not deploy artificial intelligence for pricing strategies.

This interesting work finally demonstrates the material extraneousness of AI presence in pricing setting mechanism, at least in a well-defined industrial segment (low quality hotels in the area of investigation).
In fact, the differentiating element of this paper is that it is based on consistent empirical evidence: it certainly represents a clear, consistent and tangible step forward that can and must be taken into consideration.
The possibility of using online booking platforms, instead of classic corporate websites, can facilitate the work of price comparison and sample organization.
In this sense, it is clear that this type of work could be a useful tool also for analyzing the phenomenon in other industries and geographical area.

Conclusion

What emerges from this literature review is a quite complex and fragmented picture of the phenomenon.

There is a first stand point that supports the presence of artificial intelligence in pricing mechanisms and justifies it as a tool for sustaining supra-competitive prices.
The second point of view, on the other hand, while underlining the real presence of algorithms in pricing strategies, supports the idea that these are the cause for which competitive prices can be observed.
Analyzing the literature present at the moment, it emerged that these two points of view are widely considered by scholars and that there is a growing, still new, literature in this regard. This type of wave, also looking at the media impact of the issue, seems to be widely considered also by governments and institutions.

However, it is necessary to underline that these two points of view are certainly not the only ones found in the present literature.
In fact, following what has been described in this work, it would seem that the concerns and the amount of attention paid to the presence of AI in pricing strategies could actually be exaggerated: the impact of such technologies does not seem to be a totally pervasive phenomenon in the all industries.
It has been empirically demonstrated that, for example, in the case of hotel prices, the presence of algorithms is very limited and, in some cases, even absent.

In this situation in which literature seems to be very divided between different stand points, it is nevertheless important to frame why these divergences exist and what are the condition under which we need to expect a certain price outcome rather than others.
In this sense, regarding the two stand points that marry the idea of the effective presence of AI for price mechanisms, I have identified 3 macro-conditions that can explain the sustaining of collusive or eventually competitive prices.

Firstly, from the various revised papers, it appears that the level of market transparency plays an absolutely important role.

In particular, the possibility of having access to information on competitors, on the sector in which a company operates and on macro-economic factors, appears to be a pivotal condition to be taken into consideration.
This is due to the fact that machine-learning algorithms base their accuracy on input[13]. This implies that a change in the volume and quality of information can eventually affect prices' level.
In this sense, we can expect that an improvement in the information available for AI solutions can enhance the final prices prediction and so the possibility of customizing prices, setting them at a supra-competitive level.
This type of scenario, however, leads to a second opposite finding, according to which the possibility of sustaining these prices would increase the incentive of companies to deviate from them, trying to obtain market share by bringing the price to a competitive level.
This suggests the level of market transparency can have a dual and opposite effect on prices.

This first factor is conditioned by a second one, namely the number of players in each market. In this sense, from the available literature, it emerges that also the quantity of players in a given market can influence the pricing strategies, even when algorithms are put in place.
In particular, an increase in competing players is directly linked to a decrease in the possibility of colluding on supra-competitive prices.
Conversely, when a market is concentrated, prices set via AI seem to return significantly higher prices to adopters.
This is due to the fact that the level of communication among algorithms that are put in place by companies change according to their numerosity: a lower number of participants in the price competition will drive the algorithms to better observe the others strategies. This implies that there will be room for cooperation in sustaining supra-competitive prices. On the other hand, when the number of firms adopting artificial intelligence solutions for pricing increases, this definitely leads to a disturbed communication and to subsequent lower price level.
Therefore, it is reasonable to think that, even pricing strategies coming the most advanced technologies, in reality, are still strongly impacted by the number of competing firms, as it was already mentioned in classic models.
The third condition, which I consider strongly impactful, is whether, in a specific market, there is the presence of players who all adopt AI for pricing mechanisms or, on contrary, if there are some who can adopt it and others who do not.

[13] As stated in the first chapter, the machine learning input are represented by information.

The fact that there is heterogeneity in the adoption of artificial intelligence implies strong backlashes on price levels.
When two firms compete in prices but only one of them adopts algorithms for its pricing strategies, the effects on the final price of both firms can be broken down into two periods.
More in detail, in the short-term, non-adopters, after observing the price the other firms, set its price according to the algorithm-based one.
Therefore, in this phase, there will be the possibility of sustaining a supra-competitive price given the possibility of the adopters to foresee the demand and set the prices accordingly.
In the long run, however, a price war begins and this lead both adopters and non-adopters to set competitive prices.
Hence, the difference in technologies adopted by companies leads to the same price, suggesting that the inequality related to the adoption of AI is not always related with differences in prices level.

In order to give the reader a broader and more truthful interpretation of the phenomenon possible, I decided, given the absence in the previous papers, to look for empirical evidences that would ensure, or not, the presence of algorithms in the price mechanisms.
In this sense, despite the difficulty in finding them, I thought it was useful to point out that the presence of AI in the price mechanisms is over-estimated.
What emerges is in fact a picture in which, at least in restricted sectors such as the hotel industry, the usage of technologies such as prediction machines is really restricted.
In particular, the evidence explains that only some players, such as well-structured companies, could eventually use algorithms to decide their pricing strategies.
In this sense, it is important to highlight two aspects.
The first is that, given the current information availability, AI presence in companies is not ensured. This is due to the fact that there is a lot of aversion to sharing information on pricing policies (given their strategic value) and to discussing the real use of artificial intelligence solutions, in particular on this type of activity
The second is that we can confirm that algorithmic system are definitely not very common. What emerges from the last chapter implies that there is the possibility of using AI but that this is reduced to a few businesses. Therefore, its impact can be considered residual compared to the attention currently paid to it.

From this literature review it comes out that the topic related with the use of artificial intelligence for pricing mechanisms is still in an exploratory phase, where the total presence of these technologies in the various sectors is still to be demonstrated.

In fact, on the one hand, at the moment, we can just rely on models that are based on strong unrealistic assumptions and on experiments run in artificial/synthetic environments.

In any case, these can certainly increase the basis for in-depth knowledge on the subject but, at the moment, they do not represent a definite validation of theories on the artificial intelligence deployment for prices.

On the other hand, there is an emerging literature that supports the idea that prices are still managed without algorithms and that the concern about the impact they may have is poorly founded.

So, to conclude, what we can hope for, for an advancement of studies on the subject, is the increase of information and data regarding the use of artificial intelligence by companies in their pricing mechanisms.

In this sense, a fundamental role will certainly be played by institutions which, through accommodating policies, will be able to help enthusiasts and scholars to deepen the topic with more and better empirical evidences.

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