

ALGORITHMIC COMPETITION

OECD Competition Policy Roundtable Background Note

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Foreword

Companies increasingly use algorithms to set prices and create or enhance new products and services. While algorithms can result in many efficiency-enhancing and pro-competitive effects, they can also be used by firms to restrict competition. Competition authorities should be aware of these risks, know how to investigate them and identify any possible harm to consumers, as well as consider how to address this harm. This background note considers these important issues.

First, it defines the term algorithm, describes different types of algorithms, explains which algorithms are the focus of this paper, recognises their many efficiency-enhancing and pro-competitive effects, and provides a summary of how prevalent they are.

Second, it maps out the various ways in which the use of algorithms can reduce competition and harm consumers. This includes both harm from competitors' coordination, such as algorithmic collusion, as well as harm from unilateral conduct, such as exclusionary and exploitative abuse. It considers example cases and how these algorithmic theories of harm can be remedied.

Finally, it describes how competition authorities can investigate cases where algorithms are relevant to the harm created. Specifically, it considers the potential use of algorithmic auditing and explainable artificial intelligence (AI). It details the various possible approaches. It sets out to what extent competition authorities could engage with, and adopt, these methods; highlighting the various challenges that authorities may face when doing so.

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1 Introduction

Companies are increasingly using algorithms and artificial intelligence ('AI'), as AI permeates more markets around the global economy. Advancements in AI, such as generative AI, have been in the headlines. Governments and policymakers around the world have been grappling with the opportunities and threats that algorithms and AI pose. Competition authorities are also engaging with these technological changes.

This paper focuses on the competition issues raised by the extensive use of algorithms, especially pricing algorithms. It doesn't consider consumer protection issues that some authorities may also face, for example through dark patterns and choice architecture. The OECD has previously considered the implications of algorithms for consumer protection (OECD, 2023^[1]) (OECD, 2022^[2]) (OECD, 2018^[3]).

In 2017, the OECD held a roundtable to discuss *Algorithms and Collusion* (OECD, 2017^[4]).¹ This naturally focused on the role that algorithms could take to facilitate collusion, especially tacit collusion. In particular, the threat posed by autonomous self-learning algorithms (such as machine learning algorithms), that have the potential to reach collusive outcomes without being explicitly programmed to do so. Algorithmic collusion continues to be a concern for enforcers.² However, subsequent experiences by competition authorities has shown that algorithmic harms to competition are not limited to coordinated effects, as this paper will explore.

In recent years, several competition authorities have published policy papers considering the relationship between algorithms and competition. Some examples include the UK (Competition & Markets Authority, 2021^[5]), Denmark (Danish Competition and Consumer Authority, 2021^[6]), Finland (Finnish Competition and Consumer Authority, 2021^[7]) (Finnish Competition and Consumer Authority, 2021^[8]), Japan (Japan Fair Trade Commission, 2021^[9]), Norway (Norwegian Competition Authority, 2021^[10]), Sweden (Swedish Competition Authority, 2021^[11]), the Netherlands (Authority for Consumers and Markets, 2020^[12]), Portugal (Autoridade da Concorrência, 2019^[13]), and a joint paper by France and Germany (Autorité de la concurrence & Bundeskartellamt, 2019^[14]). These papers have touched on several topics, including the prevalence of pricing algorithms, algorithmic theories of harm (both coordinated and/or unilateral), and how to investigate algorithms. This background paper adopts a similar scope and structure. We now consider some of the main findings from this paper.

An algorithm is essentially a sequence of operations that transform an input into an output. In practice, algorithms can have a range of functions. This paper focuses on search, recommendation, allocation, monitoring and pricing algorithms. Competition authority policy papers have given particular attention to the role of these algorithms. These algorithms can be pro-competitive and efficiency-enhancing. For example, algorithms can contribute to new and better products, lower production costs, lower barriers to entry, lower search costs, and better balance between supply and demand. However, they can also reduce competition and harm consumers.

Several competition authorities have surveyed firms to understand how prevalent algorithms are in the wider economy. Although limited to relatively small samples, the evidence suggests that firms operating online frequently use monitoring and dynamic pricing algorithms, while there does not seem to be much use of personalised pricing. However, increasing availability of data on customer characteristics makes personalised pricing more feasible.

There are several algorithmic theories of harm, including algorithmic collusion, algorithmic unilateral conduct (self-preferencing, predatory pricing, rebates and tying and bundling) and algorithmic exploitative conduct (excessive pricing, unfair trading practices, and price discrimination). Most algorithmic enforcement cases pertain to self-preferencing. The other theories of harm have few, or no, existing cases. However, the increasing adoption of algorithms may mean more of these types of cases in future.

The magnitude of the threat from algorithmic collusion by autonomous self-learning algorithms is still disputed in the academic literature and there are few known cases. Several firms using pricing software developed by the same third-party seems to be the biggest threat, as suggested by academic research into retail gasoline prices in Germany and cases in the US regarding software that recommends hotel room rates and software that recommends rents to landlords. Competition authorities could identify markets that use third-party pricing software as they may be most susceptible to coordinated conduct.

It is generally becoming accepted that it is necessary for competition authorities to examine algorithms directly to understand how they function. The complexity of algorithms varies, and some may be easier to understand than others, however algorithmic auditing and explainable AI offer techniques to investigate algorithms. These are ongoing fields of research. Unilateral conduct is easier to investigate using these methods than coordinated conduct. There are a range of approaches, but those that are most effective, will often require access to both the underlying algorithm and its input and output data.

There have now been several cases where competition authorities have successfully investigated an algorithm. Several competition authorities have created data units, hiring data scientists and technologists. The international cross-border nature of cases involving algorithms, mean that competition authorities around the world are facing similar issues. Authorities can benefit from collaboration and sharing of expertise with other competition authorities, as well as other regulators (such as financial regulators) that are also grappling with the threats posed by algorithms.

The OECD Competition Division has previously addressed issues related to algorithms in a [Roundtable on Data Screening Tools for Competition Investigations](#) (2022) (OECD, 2022_[15]), a [Roundtable on Ex ante regulation of digital markets](#) (2021) (OECD, 2021_[16]), the [OECD Business and Finance Outlook 2021](#) (OECD, 2021_[17]), a [Roundtable on Abuse of dominance in digital markets](#) (2020) (OECD, 2020_[18]), a [Roundtable on Consumer data rights and competition](#) (2020) (OECD, 2020_[19]), a [Roundtable on Hub-and-Spoke Arrangements in Competition](#) (OECD, 2019_[20]), a [Roundtable on Personalised Pricing in the Digital Era](#) (2018) (OECD, 2018_[3]), a [Roundtable on Algorithms and Collusion](#) (2017) (OECD, 2017_[4]). The [OECD Handbook on Competition Policy in the Digital Age](#) (2022) (OECD, 2022_[21]) details all of the work on digital economy that the OECD Competition Division has undertaken in recent years.³

This paper is organised as follows:

- Chapter 2 defines the term “algorithm”, details the different types of algorithms, specifies which algorithms are the focus of this paper, provides information on their prevalence, and acknowledges the pro-competitive effects that algorithms can have.
- Chapter 3 summarises the broad set of competitive harms that algorithms pose, including both coordinated conduct (such as algorithmic collusion) and unilateral conduct (such as algorithmic exclusionary and exploitative abuses). It provides examples of cases. It also sets out some of the remedies that authorities can consider.
- Chapter 4 considers how competition authorities can investigate algorithms. For example, whether it is feasible for competition authorities to directly examine an algorithm (and any related data and documentation) to identify harm to competition. It details the relevant techniques, skills authorities require, as well as the challenges an authority may face. Authorities can also learn from other regulators that may have more experience tackling these issues.
- Chapter 5 concludes.

2 Types of algorithms and their prevalence

Companies increasingly use algorithms for a variety of purposes, either to create new products, or enhance existing ones. Algorithms are the source of new online markets and are disrupting previously offline industries. Algorithms have a range of functions. Most competition authorities have focused on the use of pricing algorithms, particularly considering their potential role in algorithmic collusion and personalised pricing. This background paper considers search, recommendation, allocation, monitoring and pricing algorithms.

In this chapter, we consider the following questions:

- What is an algorithm? What are the different types of algorithms? What types of algorithms are the focus of this paper?
- How do algorithms benefit consumers?
- How prevalent are algorithms in the economy?

2.1. Definition and types of algorithms

An algorithm is essentially a sequence of operations that transform an input into an output. The definition of algorithm adopted in the OECD background note to the Roundtable on *Algorithms and Collusion* (OECD, 2017, p. 8_[4]) was:

“An algorithm is an unambiguous, precise, list of simple operations applied mechanically and systematically to a set of tokens or objects (e.g., configurations of chess pieces, numbers, cake ingredients, etc.). The initial state of the tokens is the input; the final state is the output. (Wilson and Keil, 1999_[22]).”

This definition is broad and can cover much computing technology. It may also be outdated given recent advances in AI which are increasingly complex. This paper focuses on specific types of algorithms which are of particular concern for competition policy. The classifications below, both by function and technology, provide a more concrete definition the specific types of algorithms that exist. This section then explains the subset of these algorithms that are the focus for this paper.

Algorithms are developed and used for different purposes and can usefully be classified using the following functional typology (based on (Latzner, 2019, p. 4_[23]) and (Authority for Consumers and Markets, 2020, p. 5_[12])):⁴

- **Search:** presenting and ordering information based on certain input (e.g., Google search, Bing or Baidu), which could be a search for products or services (e.g., Amazon or Booking.com).
- **Recommendation:** recommending certain information or products mostly based on data about the user (including behavioural data), the product and/or other parameters (e.g., Spotify or Netflix).
- **Allocation:** the automated execution of transactions, and the distribution and allocation of supply and demand. Think of the automated real-time bidding selling of online advertisement space (e.g.,

Google AdSense), linking a customer with an available taxi (e.g., Uber), or algorithmic trading (e.g., Quantopian).

- **Surveillance or monitoring:** the observation of behaviour and patterns to identify deviations which could include fraud detection in transaction data, employee monitoring (e.g., Spector, Sonar Spytec) or general monitoring software (e.g., Webwatcher). It could also relate to market monitoring to track the behaviour and strategic decisions of competitors, such as prices (e.g., Wiser Solutions or Intelligence Node).
- **Pricing:** set or recommend prices using data on observable customer characteristics or market conditions (e.g., the Rainmaker Group or A2i Pricecast Fuel).
- **Aggregation:** the collection, categorisation, and reordering of information from different sources. For example, news aggregators (e.g., Google News or nachrichten.de)
- **Communication:** automated communication with consumers and/or businesses. Think of the communication between consumers and chatbots or virtual assistants that communicate with third parties on behalf of consumers (e.g., Siri, Alexa or Google Assistant).
- **Filters:** the filtering (mostly in the background) of information and data. For example, think of spam filters or filters to exclude copyrighted material (e.g., Norton or Net Nanny).
- **Information production:** the production of information. Think of automated news reporting, or automated reporting about sports events, stock markets, and share prices (e.g., Quill, Quakebot or GPT-4).
- **Prediction:** predicting future behaviour or scenarios (e.g., PredPol, Sickweather or scoreAhit).
- **Scoring:** the scoring or ordering of information, products, businesses and/or consumers. Think of online review scores (e.g., eBay's reputation system) and credit scores of consumers (e.g., Kreditech).

This paper focuses on search, recommendation, allocation, monitoring and pricing algorithms. Competition authority policy papers have predominantly focused on these types of algorithms (for example, (Autoridade da Concorrência, 2019, p. 41_[13])).

Algorithms can also be classified by type of technology. These algorithms are mostly based on artificial intelligence (AI), machine learning and deep learning. The OECD has considered the relationship between these terms previously (OECD, 2017, pp. 8-11_[4]), and this classification remains relevant for the algorithms considered in this paper.

Artificial intelligence (AI) is the science and engineering of making intelligent machines, while machine learning is a specific sub-field of AI that tries to create intelligent machines using algorithms that iteratively learn from data and experience (OECD, 2017, p. 9_[4]). Deep learning is a sub-field of machine learning (and thus a sub-field of AI) that broadly replicates neurons in the human brain through an artificial neural network (OECD, 2017, p. 11_[4]).

There are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning (OECD, 2022, pp. 16-17_[15]). Supervised learning involves the algorithm learning from training data – which is data that maps a relationship between existing inputs and outputs - to predict an output using new input data. Unsupervised learning involves the algorithm learning a structure directly from the input data, for example, clustering the input data into groups. Finally, reinforcement learning involves the algorithm effectively using a ‘trial and error’ approach, changing the input values and observing the outcome of a reward function, aiming to maximise this reward.

Deep learning algorithms typically have several layers of artificial neural networks. Deep learning is useful for the most complex problems that involve large and multidimensional datasets such as text, voice, images and videos (França, 2021_[24]). In machine learning, when using large datasets with many variables, it can be time-consuming for an analyst to select the relevant features (which can be original variables or

combinations of several of them) to use in the model. Deep learning can automate this feature selection, reducing the time and costs of feature selection (OECD, 2017, pp. 10-11^[4]). However, this makes it difficult to know which features the model has relied on and how they were weighted, reducing interpretability, transparency and explainability, making it harder to understand how a deep learning model came to a decision, and thus deep learning algorithms are typically more difficult to audit (see Chapter 4).

AI foundation models⁵ (which underpin generative AI)⁶ have been garnering particular attention with recent high-profile releases, such as OpenAI's ChatGPT and Google's Bard.⁷ GPT-4, OpenAI's most recent release, is a multimodal large language model (accepting image and text inputs, emitting text outputs) that uses deep learning (a subfield of AI and machine learning) to predict a sequence of words to produce text output.⁸ While the technology is not new, policy discussions are still ongoing, with warnings of the antitrust risks of generative AI,⁹ and more broadly, considering how generative AI algorithms should be regulated¹⁰ (and to what extent that may be similar to search and recommendation algorithms).¹¹ There have even been calls from tech researchers and executives to pause developments in AI more powerful than GPT-4 to give time to assess the potential threats that they pose.¹² The OECD set out the technological, socio-economic and policy considerations of AI language models in a recent paper (OECD, 2023^[25]). The UK Competition and Markets Authority (CMA) recently announced it is launching a review of the market for AI foundation models to understand how their use could evolve, what opportunities and risks these could bring, and what competition and consumer protection principles can best guide these markets going forward.¹³

While not covered further directly in this paper, competition authorities should also be aware of several new technologies. For example, the UK Digital Regulation Cooperation Forum (DRCF) previously set out example areas for further research, which are new or rapidly developing technologies or markets, including: (i) Artificial Intelligence (AI) technologies (including machine learning and deep learning); (ii) Privacy enhancing technologies; (iii) Distributed ledger technologies (such as blockchain) which can be used to achieve Web 3.0; (iv) Cloud computing technology; (v) Quantum technologies; (vi) 'Internet of Things' (including voice assistants and wearable technologies); (vii) Cybersecurity technologies; (viii) Immersive technologies (including virtual and augmented reality technology); (ix) Advertising technologies; and (x) Biometric technologies (Digital Regulation Cooperation Forum, 2021^[26]). Academic literature also provides some simple introductory descriptions of new technologies such as blockchain, artificial intelligence and cloud computing (Butijn, 2023^[27]).

2.2. Benefits of algorithms

Algorithms provide benefits for consumers, enable the creation of new markets, and disrupt existing markets (Competition & Markets Authority, 2021^[28]). New digital products have improved living standards and are valued by consumers. For example, researchers found that search engines were the most popular digital goods category in 2017, with the average user valuing access to the search engine at 17 530 USD (Brynjolfsson, 2019, p. 7252^[29]). Digital products represent an increasing share of the global economy. AI has grown considerably in recent years, and this growth is expected to increase in the rest of this decade.¹⁴

Algorithms provide many efficiency-enhancing and pro-competitive effects (Descamps, 2021, pp. 35-36^[30]), including both demand-side and supply-side efficiencies (OECD, 2017, pp. 14-18^[4]). It is widely accepted that pricing algorithms can create substantial efficiency gains and reduce transaction costs (Assad et al., 2021, p. 4^[31]).

There are several ways in which algorithms can be efficiency-enhancing and pro-competitive. First, they can be the basis of disruptive innovation that results in new or improved products. For example, products can be personalised and tailored to the specific needs of the consumer. Second, they can reduce costs through improved production processes or more productive workers. Third, they can reduce barriers to entry by allowing smaller new entrants to gain market insights or develop new disruptive products at lower

cost. Fourth, algorithms can reduce customer search costs by providing consumers with a range of suitable products with comparable information on the key dimensions of competition (such as price, quality and consumers' preferences). For example, price comparison websites provide consumers with an instant comparison of prices across a range of goods and services, price monitoring tools can inform customers when prices are particularly low, and AI is even being used for product recognition to enable consumers more easily find precisely what they are looking for.¹⁵ Finally, algorithms can better balance supply and demand. Dynamic pricing can optimise pricing to reflect changes to market conditions.

However, despite their many pro-competitive effects, algorithms can also reduce competition and harm consumers. The next chapter details these potential competitive harms. Before that, the following section considers the prevalence of algorithms, particularly pricing algorithms.

2.3. Prevalence of pricing algorithms

The use of algorithms is transforming markets around the world. Algorithms are adopted in both online and offline markets.¹⁶ While a comprehensive overview of the reliance on algorithms is not available, there is now some evidence from specific surveys from researchers and competition authorities. These surveys focus on pricing algorithms.

Much of the literature focuses on the use of algorithms to monitor and set prices. It is important to distinguish between pricing algorithms that monitor other firms' prices (price monitoring algorithms), those that recommend or automatically set a price based on other firms' prices and/or market conditions such as demand (dynamic pricing algorithms), and those that tailor prices to specific individuals based on their features (personalised pricing algorithms). (Seele et al., 2021^[32]) provide a review of academic articles on dynamic and personalised pricing algorithms. (Gautier, Ittoo and Van Cleynenbreugel, 2020^[33]) also consider the prevalence and current technological capabilities of pricing algorithms.

The OECD considered personalised pricing at a previous roundtable and found that it was difficult to determine how common personalised pricing was given most examples were anecdotal (OECD, 2018, pp. 14-17^[3]). In the intervening period, there have been several surveys by competition authorities and researchers trying to investigate the prevalence of pricing algorithms. These surveys are summarised in Annex A. The surveys suggest a substantial minority of firms use pricing algorithms, although there is little evidence of personalised pricing. Separately, there is evidence to suggest that the use of pricing algorithms has been rapidly increasing in both online and offline markets.¹⁷

Annex A contains a sample of studies by competition authorities and academic researchers. The competition authority studies are mostly European (EU, Denmark, the Netherlands, Norway, Portugal and the UK). The academic research included is for non-European jurisdictions (Singapore and the US). These studies are typically surveys of a sample of firms in the given jurisdiction. They are usually one-off surveys, that provide a single snapshot in time, conducted over a single one- or two-month period. The year of the collection period depends on the jurisdiction, but ranges from 2015 to 2021. The surveys typically focus on a sample of firms with an online presence (ranging from 38 to thousands of firms). Some surveys sample firms from across the economy, while other surveys focus on sectors that have many firms with an online presence.

The relatively small sample of studies in Annex A does not provide conclusive evidence on the prevalence of pricing algorithms. The studies are too sparse and infrequent to make general conclusions. Nonetheless, while it varies by jurisdiction, the evidence in Annex A suggests that: (i) a substantial minority of firms across the economy use price monitoring algorithms (mostly with an online presence); (ii) of which, most of these manually adjust their prices or use a dynamic pricing algorithm for price recommendations, while only a small proportion use an algorithm to automatically update their prices; and (iii) there does not seem

to be much evidence of personalised pricing. In other words, price monitoring algorithms and dynamic pricing algorithms are relatively common in online markets, while personalised pricing is not.

There are also several market research reports that review the vendors supplying price optimisation and management software, both for the business to business (B2B) market (Gartner, 2022^[34]) and the business to consumer (B2C) retail market (IDC, 2019^[35]). Retail pricing algorithm software seems to be targeted at several offline industries, some of the most common being groceries, fashion/clothing, department stores (IDC, 2019, p. 17^[35]). The adoption of B2B pricing algorithms appears to be widespread, with an estimate of 1,800 companies globally using the software in 2020 (Gartner, 2022, p. 5^[34]). Software vendors claim that adopting the technology delivers increased revenue and margins.¹⁸

As detailed above, there does not appear to be much evidence of widespread personalised pricing. Behavioural economics suggests that consumers do not like personalised pricing. Consumers have accepted third-degree price discrimination,¹⁹ such as seniors and children paying a lower ticket price, where cultural norms have been established. However, consumers appear to generally dislike personalised pricing, particularly due to the lack of transparency. Therefore, firms may either refrain from adopting personalised pricing to protect their reputation or be less forthcoming and open when they do use personalised pricing. This may explain why there is not much evidence of firms using personalised pricing (Botta and Wiedemann, 2020, pp. 388,400^[36]).

3 Algorithmic theories of harm

Algorithmic theories of harm consist of both coordinated conduct (algorithmic collusion) and unilateral conduct (algorithmic exclusionary and exploitative conduct). This chapter makes a clear distinction between pricing algorithms, which can facilitate both these types of conduct, and other types of algorithms (such as search, recommendation and allocation algorithms) that can also result in unilateral conduct harms. This chapter maps out each algorithmic theory of harm. It also provides supporting academic literature and example cases (where available). Many of these competition concerns are not new and have been discussed at previous OECD roundtables,²⁰ but firms can use algorithms to adopt these business practices at a larger scale and faster pace, thus increasing the feasibility and efficacy of these harms.

Most existing algorithmic cases pertain to self-preferencing; and even these cases have been relatively few. There have also been some cases where algorithms have either facilitated an explicit collusive agreement or where pricing software has been provided by the same software provider (effectively resulting in a hub and spoke setting). As far as the Secretariat is aware, there have not been any autonomous tacit collusion cases, algorithmic predatory pricing, algorithmic rebate, algorithmic tying and bundling. There have also been very few algorithmic exploitative abuse cases. Nonetheless, these harms are theoretically possible and there may be cases in the future.

In this chapter, we consider the following questions:

- How can algorithms reduce competition and harm consumers?
- Are there examples of such algorithmic cases?
- How can authorities remedy these algorithmic theories of harm?

3.1. Algorithmic coordinated conduct

There is a concern that pricing algorithms can facilitate coordinated conduct that results in inflated prices. There are broadly three main ways that algorithms can help to facilitate collusion (Competition & Markets Authority, 2021, p. 30_[5]) (Li, Xie and Feyler, 2021, pp. 2-3_[37]):

- **Algorithms that facilitate explicit collusive agreements:** Automated pricing systems based on available pricing data can detect and respond to pricing deviations, making explicit collusion between firms more stable (such as to implement resale price maintenance or a price fixing agreement).
- **Algorithms in hub and spoke settings:** Several firms using the same third-party pricing software that determines their pricing decisions, resulting in a hub and spoke setting that can facilitate information exchange.
- **Algorithmic autonomous tacit collusion:** Self-learning autonomous algorithms can decide to collude (or at least avoid reaching a competitive outcome) without information sharing or explicit coordination.

The specific ways in which pricing algorithms (notably monitoring algorithms, parallel algorithms, signalling algorithms, and self-learning algorithms) can facilitate collusion are set out in the OECD background note on *Algorithms and Collusion* (OECD, 2017, pp. 18-32_[4]). While there were early accounts of the potential

for algorithmic autonomous tacit collusion by legal scholars (Ezrachi and Stucke, 2015^[38]) (Ezrachi and Stucke, 2016^[39]) (Mehra, 2016^[40]), it is only relatively recently that economists have started to work on this topic (Assad et al., 2021, p. 5^[31]). However, despite the now considerable research on algorithmic collusion (see (Van Uytsel, 2018^[41]) for a literature review), its feasibility and scale in practice are still relatively unclear. While the adoption of pricing algorithms has grown considerably, they are not yet universal, never mind the use of self-learning pricing algorithms (see Chapter 2 above). Even if firms use self-learning pricing algorithms, there is not conclusive evidence that algorithmic autonomous tacit collusion is a significant issue. Nonetheless, competition authorities should remain vigilant (Deng, 2020, p. 968^[42]).

Economists initially considered that algorithmic collusion was unlikely without explicit communication,²¹ or even if tacit, was unlikely to occur in dynamic real world market conditions (Schwalbe, 2018^[43]) (Assad et al., 2021, p. 5^[31]). However, recent literature has questioned this assumption.

There is literature suggesting algorithmic collusion is certainly possible without communication and provides some initial indications to suggest that it is already occurring. While personalised pricing is usually based on supervised machine learning (such as regression analysis), algorithmic autonomous tacit collusion is usually modelled using reinforcement learning algorithms (i.e., algorithms that learn through autonomous trial and error exploration) (Gautier, Ittoo and Van Cleynenbreugel, 2020, p. 431^[33]). Several authors used Q-learning reinforcement learning algorithms finding that these algorithms learn to set supra-competitive prices without communicating with each other (Calvano et al., 2020^[44]) (Klein, 2021^[45]) (Ballester, 2021^[46]). Furthermore, in the first of its kind, a recent empirical academic paper found that the adoption of third-party pricing software by petrol stations in Germany inflated prices in local markets for retail gasoline (see Box 3.1). However, other authors, also using Q-learning reinforcement learning, argue convergence to a collusive equilibrium is slow and often unsuccessful (den Boer, Meylahn and Schinkel, 2022^[47]).

Some authors have even found that pricing algorithms can soften competition by undermining the incentives of competitors to undercut prices, knowing that any reduction in price will be met instantly by an equivalent cut in price. This means that prices across the market may be inflated relative to the counterfactual without pricing algorithms, even in the absence of collusion (Brown and MacKay, 2021^[48]).

In general, some authors consider the risks posed by algorithmic collusion are overstated and that continued research and enforcement efforts may be unwarranted (Schrepel, 2020^[49]), while others consider that the lack of cases is misleading and it should remain a key priority (Klein, 2020^[50]).

There have been relatively few cases of algorithmic collusion. Nonetheless, some authorities have indicated concern about the potential risk of algorithmic collusion.²² The known cases consist of both horizontal and vertical coordination (such as resale price maintenance (OECD, 2019, p. 28^[20])). Resolved cases include: (i) online poster retailers used simple pricing algorithms to coordinate prices (Topkins US and GB Eye Trod UK)²³; (ii) online travel platform facilitated collusion emailing travel agents that it was capping discounts (Eturas)²⁴; (iii) Spanish real estate firms used a common brokerage software to coordinate prices (Propotech)²⁵; and (iv) electronics manufacturers restricted retailers from independently setting sales prices (resale price maintenance) thus keeping them inflated (Consumer Electronics case)²⁶ (Klein, 2020^[50]) (Braeken and Versteeg, 2022^[51]).

Third-party pricing software was again under the lens in recent complaints of algorithmic collusion in the US and a recent academic paper suggesting signs of algorithmic collusion. There have been allegations that hoteliers on the Las Vegas strip used third-party pricing software set supra-competitive prices (see Box 3.2). In a separate case, renters filed federal lawsuits in the US alleging that RealPage's YieldStar software, that recommends rent prices to landlords, may facilitate price coordination among landlords.²⁷

In another recent case involving third-party pricing software, the software creators were absolved of any wrongdoing. In June 2018, in a complaint filed in France, the allegation was that third-party pricing software

enabled competing car manufacturers to coordinate prices for spare parts.²⁸ But in November 2022, the accused were exonerated of any wrongdoing and avoided a fine.²⁹

Even if an authority identifies a potential case of algorithmic collusion, some commentators have suggested that there is a potential enforcement gap. Algorithmic autonomous tacit collusion may go unpunished if there is a lack of explicit communication. This was touched on at the previous OECD roundtable on *Algorithms and Collusion* (OECD, 2017, pp. 36-39^[4]), and has been raised again in recent academic literature (Mazundar, 2022^[52]).

There have been several calls to action for policy change to address this potential enforcement gap in the academic literature.³⁰ Furthermore, in a recent public consultation,³¹ the UK CMA asked whether its role and suggested response to algorithmic theories of harm was “*effective and proportionate*”. The responses generally suggested that most algorithmic theories of harm are already captured by existing law. The main exception was algorithmic autonomous tacit collusion, where some considered the current focus on communication between competitors may not be sufficient in cases where humans are not directly involved (Competition & Markets Authority, 2021, pp. 13-14^[53]).

Existing competition law already sufficiently captures cases where an algorithm simply facilitates an explicit collusive agreement between humans (e.g., where the algorithm facilitates coordination or an agreement between firms, or the pricing software has the same supplier). However, in the case of tacit collusion, existing competition law may not be sufficient, and algorithmic autonomous tacit collusion may not be captured. This could be addressed by changing the definition of ‘agreement’ and ‘concerted practice’ to move away from being defined by ‘act of reciprocal communication between firms’ or ‘meeting the minds’ (Caforio, 2022^[54]).

Alternatively, identifying facilitating practices could capture some instances of algorithmic collusion. Facilitating practices are actions that may increase the likelihood that competitors can achieve coordination. Facilitating practices can reduce barriers to coordination and increase incentives for competitors to cooperate. In the context of algorithmic collusion, facilitating practices could pertain to competitors exchanging information on the kinds of datasets used by their algorithm, output or cost data, or the decisional parameters included in the algorithm. However, facilitating practices can also be pro-competitive, for example if they provide consumers or new entrants with information to make better decisions. Facilitating practices are usually treated as plus factors which, under certain circumstances, serve as indirect indications of an “agreement”. Although, given the potential shortcomings of existing law to address algorithmic collusion, it may be a good time to reconsider whether the adoption of facilitating practices, by itself, could be a basis for liability (Gal, 2019, pp. 103-104^[55]).

Setting the sufficiency of competition law to one side, if algorithmic collusion is (or becomes more) prevalent, authorities should consider proposals to remedy it. For example, Michal Gal has made several proposals to address algorithmic collusion, including a market-based approach and three regulatory interventions: (i) algorithmic consumers, which do not require regulatory intervention, but aggregate consumers into buying groups to give them buyer power, can break coordination between sellers by increasing the incentive to deviate with a lower price (for a large quantity); (ii) merger review, which could prohibit, or remedy, mergers that increase the risks of algorithmic collusion without any offsetting benefits; (iii) a disruptive algorithm, where a regulator designates (and subsidises) one supplier to operate a disruptive algorithm, to charge lower, potentially competitive prices, creating noise on the supply-side and disrupting the coordination; and (iv) enforce a time-lag in pricing algorithms’ response to market conditions, freezing the price of one supplier in each period (i.e., the lowest priced supplier) which would incentivise the other suppliers to price below this firm to capture extra capacity (Gal, 2022, pp. 22-36^[56]).

Alternatively, a regulatory approach could address the issues of algorithmic collusion through: (i) ex-ante influence on the design of algorithms such that they avoid tacit collusion; and (ii) adopting regulation to reduce prices to competitive levels if they increase to potentially collusive levels following the introduction of algorithmic pricing software (Caforio, 2022^[54]). And finally, others have suggested that digital platforms

may be able to disrupt collusion between online sellers on their platform by steering consumer demand using their platform design rules (e.g., how they rank or display products to consumers) (Johnson, Rhodes and Wildenbeest, 2020^[57]).

Box 3.1. Empirical evidence suggesting algorithmic collusion in the German gasoline retail market

A recent academic paper provided the first empirical analysis of the relationship between algorithmic pricing and competition. While economic theory often provides ambiguous and conflicting predictions about the relationship, this paper found that the adoption of algorithmic pricing significantly impacted competition, shown by higher margins in non-monopoly markets where algorithmic pricing was adopted. The authors found that margins increased 28% in local duopoly retail gasoline markets in Germany when both firms adopted algorithmic pricing software, while there was no price change in local monopolies (where competition was unchanged).

The authors used comprehensive high frequency pricing data from German gasoline retailers. The price data was for all most common fuel types (Super E5, Super E10, and Diesel), at 1-minute intervals, from the start of 2014 to the end of 2019, for every petrol station in Germany (16,027 stations). The authors use two geographic market definitions: (i) drawing 1KM radii around stations; or (ii) using 5-digit ZIP codes.

The authors considered that there are two potential mechanisms through which the adoption of the pricing algorithms could have led to an increase in prices. Pricing algorithms could: (i) fail to learn to compete effectively (e.g., not best respond to competitors' prices); or (ii) learn how not to compete (i.e., tacitly collude). The latter would be most concerning for competition policy.

The paper finds pricing algorithms can learn tacitly collusive pricing strategies which are currently legal in most jurisdictions, given it is normally difficult to establish a collusive agreement without explicit communication. The same pricing software is available and increasingly used around the world, in a range of industries. The main policy implication is that the authors recommend competition authorities work to understand the relationship between algorithmic pricing and competition in these various contexts.

Source: Assad, S., Clark, R., Ershov, D., & Xu, L. (2020). Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market. https://www.econstor.eu/bitstream/10419/223593/1/cesifo1_wp8521.pdf

Box 3.2. Class action complaint regarding the rental of hotel rooms on the Las Vegas strip

On 25 January 2023, claimants filed a class action complaint at the United States District Court of Nevada. The relevant market is that for the rental of hotel rooms on the Las Vegas strip.

The case has been brought against defendants who manage hotels on the Las Vegas strip (including Caesars Entertainment, Inc., Treasure Island, LLC, Wynn Resorts Holdings, LLC, and MGM Resorts International). While the case is ongoing, it provides an interesting example of an alleged hub-and-spoke conspiracy.

The defendants used three algorithms from the third-party provider (the Rainmaker Group): (i) GuestRev; (ii) RevCaster; and (iii) GroupRev. GuestRev is an algorithm specifically tailored to the casino hotel market that recommends prices for individual hotel rooms. The Rainmaker Group boasted on their website that the software had a 90% acceptance rate for these price recommendations. RevCaster allows clients to monitor and respond to competitor pricing, by collecting market-specific price data from competitors. Finally, GroupRev is an algorithm that forecasts demand for customers that book in groups (for example, groups of 10 or more attending conferences or conventions). The use of these algorithms allegedly allowed the defendants to increase their prices at the expense of consumers.

The allegation is that the defendants used third-party pricing software to aggregate their pricing strategy information and receive price recommendations from the software. In effect, the defendants replaced their independent pricing and supply decisions with a shared set of pricing algorithms that allegedly allowed the defendants to collect supra-competitive prices for their hotel rooms. While the defendants didn't directly share their pricing strategies or intended pricing decisions, that information still ended up in common hands, which was then allegedly used to maximize market-wide prices, in effect, an alleged hub-and-spoke conspiracy.

Notes: The case is "Richard Gibson and Heriberto Valiente v. MGM Resorts International et al, U.S. District Court, District of Nevada, No. 2:23-cv-00140".

Source: <https://www.classaction.org/media/gibson-et-al-v-mgm-resorts-international-et-al.pdf>

3.2. Algorithmic unilateral conduct

In 2017, the OECD roundtable on *Algorithms and Collusion* (OECD, 2017^[4]), focused on the potential of algorithms to facilitate collusion (whether explicit or tacit). The debate about the implications of algorithms on competition law enforcement has mostly focused on algorithmic collusion thus far (Cheng and Nowag, 2022^[58]). However, dominant firms can also use algorithms to engage more effectively in unilateral conduct (i.e., abuse of dominance). This section details these potential concerns.

This section is organised into algorithmic exclusionary conduct and algorithmic exploitative conduct. Algorithmic exclusionary conduct pertains to: (i) self-preferencing; (ii) predatory pricing; (iii) rebates; and (iv) tying and bundling. Algorithmic exploitative conduct relates to: (i) excessive pricing; (ii) unfair trading conditions; and (iii) price discrimination.

3.2.1. Algorithmic exclusionary conduct

Exclusionary conduct by a dominant firm indirectly harms consumers through the exclusion of competitors in the market. A dominant firm can engage in algorithmic exclusionary conduct, when its algorithm

forecloses a competitor (either partially or fully), preventing the competitor from challenging the dominant firm's market position.

Search, recommendation and allocation algorithms

Self-preferencing

This paper defines self-preferencing as a dominant firm favouring its own (or affiliated) products and services over rival competitors, meaning the ranking is not based on 'competition on the merits'. The welfare effects of self-preferencing are ambiguous (Bougette, Budzinski and Marty, 2022, p. 202^[59]). There may be situations in which self-preferencing does not reduce competition. However, the concern is that the firm will leverage its dominance in one market to foreclose a rival in a related market (either downstream or in a complementary market). This harm has mostly been considered in the context of search, recommendation, and allocation algorithms.

Jurisdictions around the world have considered self-preferencing cases. For example, in Asia, the Korean Fair Trade Commission (KFTC) sanctioned Kakao Mobility ('Kakao') for conduct on their Korean taxi app. The KFTC found that Kakao had leveraged their market power in the general call market to increase their market power in the taxi franchise market (see Box 3.3 below). Furthermore, in Europe, there have also been several self-preferencing cases, such as: (i) EC Google Shopping; (ii) EC Amazon "Buy Box" and Prime Label (see Box 3.4 below); and (iii) AGCM Amazon logistic services. These cases provide several possible rationales for self-preferencing that excludes competitors.

One rationale is imperfect rent extraction (e.g., EC Google Shopping) (Motta, 2022, pp. 8-10^[60]). For example, Google monetises through search advertising, meaning that users and sellers do not pay for the appearance of links in organic search results, which may incentivise Google to manipulate its search algorithm to foreclose rivals competing with its own services. Google was dominant in search. Google displayed its comparison shopping service ('CSS') more favourably than rival CSS's and manipulated its search algorithm to demote rival CSS's in organic search results. This led to reduced visibility and traffic for rival CSSs (which they couldn't replace using other sources), excluding them from the market.

Another rationale is a dominant firm using its algorithm to engage in customer foreclosure that raises rivals' costs (e.g., AGCM Amazon) (Motta, 2022, pp. 28-29^[60]). Amazon was dominant in marketplace. The Buy Box features on the Amazon marketplace and is an important channel to market for marketplace sellers. Amazon improved the chances of a marketplace seller appearing in the Buy Box if it purchased Amazon's logistics offering: Fulfilment by Amazon (FBA) (where Amazon stores, picks, packs, delivers and provides customer service for Amazon marketplace sellers' products³²). This meant fewer customers available for competing logistics companies to amortise their fixed costs and guarantee an appropriate quality of service. In this way, Amazon raised the costs of rival logistics companies, foreclosing them from the market.

There are several possible ways to remedy self-preferencing suggested in the academic literature: (i) using remedies, commitments³³ or interim measures³⁴ following case-by-case effects-based assessment; (ii) use of per se rules to prohibit self-preferencing; or (iii) structural or functional separation of the platform from the line of business that sells the competing product (Bougette, Budzinski and Marty, 2022, pp. 204-205^[59]). Other authors consider that a mechanistic application of self-preferencing (i.e., prohibiting self-preferencing outright) could be to the detriment of consumers in the long run, as doing so could be seen as a regulator picking a particular market design (Peitz, 2022, p. 28^[61]).

Box 3.3. KFTC sanctioned Kakao in self-preferencing case

On 14 February 2023, the Korea Fair Trade Commission (KFTC) imposed a corrective order and a fine of 25.7 billion won (approximately, 20 million USD) on Kakao Mobility ('Kakao') for manipulating its taxi distribution algorithm to favour Kakao T Blue affiliated taxis over non-affiliated taxis ('non-member drivers').

Kakao T is a Korean taxi app, that is a platform, matching passengers with taxi drivers. Passengers can request a taxi using Kakao's general call service ('general call market'), and both Kakao T Blue affiliated taxis ('member drivers') and non-affiliated taxis ('non-member drivers') can respond to the request on the Kakao T app and provide the passenger with a taxi ride. In 2019, Kakao had considerable market power in the general call market, with a market share of 92.9%.

Taxi drivers can work independently, or they can work for a taxi franchise ('taxi franchise market'). Kakao T Blue was Kakao's taxi franchise offering. Taxi drivers could become Kakao T Blue member drivers for a fee, in exchange for rapid dispatch, clean and neat uniforms, continuous and systematic quality management, and automatic payment systems. Kakao T Blue member drivers exclusively used the Kakao T app to book passengers. In 2019, Kakao only had a market share of 14.2% in the taxi franchise market.

Kakao manipulated its algorithm in two ways that benefited its member drivers. Kakao did this with the aim of increasing its number of member drivers. First, Kakao's algorithm assigned general call passengers to member drivers before non-member drivers. Second, Kakao allocated less profitable short distance journeys, that were less than 1km, exclusively to non-member drivers. These two actions resulted in higher incomes for member drivers, incentivising non-members to sign up to Kakao T Blue.

Kakao leveraged its market power in the general call market to increase its market power in the taxi franchise market. Kakao's actions made it harder for competitor taxi franchise companies to attract drivers, foreclosing rivals in the taxi franchise market. Kakao significantly increased its market share in the taxi franchise market, from 14.2% in 2019 to 73.7% in 2021, effectively eliminating rivals whose franchise taxis have become hard to find. Kakao maintained its market power in the general call market, growing its market share from 92.9% in 2019 to 94.46% in 2021, increasing the likelihood that it could put up its passenger and driver app usage fees. This case demonstrates how a firm dominant in one market can exploit its market power to stifle competition in a related market.

Source: http://www.ftc.go.kr/www/selectReportUserView.do?key=10&rpttype=1&report_data_no=9946

Box 3.4. European Commission “Amazon Buy Box” case

Amazon operates a dual role as a marketplace and retailer. As a marketplace, Amazon acts as a platform, bringing together consumers and third-party sellers. The Amazon “Buy Box”, which appears on Amazon’s marketplace website, prominently features a single seller’s offer and allows the customer to quickly purchase the product by clicking on a buy button. The “Buy Box” is an important channel for marketplace sellers to reach consumers.

In July 2019, the European Commission (EC) opened a formal investigation into Amazon’s use of non-public data on third-party retailers, the “Amazon Marketplace” case (AT.40462). On 10 November 2020, the EC opened another investigation, this time into whether the criteria that Amazon uses to select the winner of the “Buy Box” and enable sellers to offer products under the prime programme, lead to preferential treatment of the Amazon’s retail business and sellers that use Amazon’s logistics and delivery services, the “Amazon Buy Box” case (AT.40703).

The EC established that Amazon holds a dominant position in the national markets for the provision of marketplace services in at least Germany, France and Spain. As a retailer, Amazon’s retail business competes with third-party sellers. The EC found that Amazon’s algorithm unduly favoured its own retail business, as well as third parties that use Amazon’s logistics and delivery services, over other third-party retailers, when selecting the offer that would feature in the “Buy Box”. The EC preliminarily concluded that Amazon had abused its dominance. The EC determined that Amazon could leverage its dominance in the market for marketplace services to the retail market, through self-preferencing in the “Buy Box”, which had the effect of excluding third-party retailers.

Amazon offered commitments to address both cases. These were market tested between 14 July 2022 and 9 September 2022, and Amazon subsequently amended its initial proposal. On 20 December 2022, the EC made these revised commitments legally binding.

The Amazon commitments to address the “Buy Box” concern were: (i) to treat all sellers equally when ranking the offers for the purposes of the selection of the Buy Box winner; and (ii) display a second competing offer to the Buy Box winner if there is a second offer from a different seller that is sufficiently differentiated from the first one on price and/or delivery. The second competing Buy Box offer will be more prominent and include a review mechanism in case the presentation is not attracting adequate consumer attention.

Sources: https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7777;
https://ec.europa.eu/competition/antitrust/cases1/202310/AT_40703_8990760_1533_5.pdf

Pricing algorithms

Pricing algorithms can be used for personalised pricing and algorithmic targeting. Personalised pricing involves tailoring prices for different consumers based on information about personal characteristics or behaviour (OECD, 2018, p. 8_[31]). Algorithmic targeting allows the firm to price differently for marginal and inframarginal customers (i.e., prices for two groups of consumers: (i) at-risk; and (ii) safe); algorithmic targeting is much less technically demanding than personalised pricing.

A firm can personalise prices or price discriminate if it has a degree of market power, a way to target customer prices, and an estimate of customer’s willingness to pay. Pricing algorithms and detailed consumer profiles are making first-degree price discrimination³⁵ more feasible.

The overall welfare effects of personalised pricing can be ambiguous (Botta and Wiedemann, 2020, pp. 386-388_[36]). Under a price-discriminating monopolist, consumers that have a lower willingness to pay

(“poorer” consumers) would pay a lower price than customers with a higher willingness to pay (“richer” consumers), resulting in a redistribution of consumer welfare. However, the monopolist could use personalised pricing to set prices at a level that is closer to consumer willingness to pay for all consumers, transferring part of consumer surplus to the monopolist (Botta and Wiedemann, 2020, p. 400^[36]). Therefore, personalised pricing does not always reduce competition and harm consumers.

However, a dominant firm can use pricing algorithms for personalised pricing or algorithmic targeting to pursue harmful exclusionary business strategies related to predatory pricing, rebates, and tying and bundling. These exclusionary theories of harm considered below are predominantly based on algorithmic targeting and detailed in (Cheng and Nowag, 2022^[58]).

Algorithmic targeting can make these theories of harm more feasible. Prior to personalised pricing and algorithmic targeting, a dominant firm trying to engage in exclusionary anticompetitive conduct would typically have to apply a single price across the market (if they were unable to price discriminate). Thus, the dominant firm would have to consider the trade-off between the increase in profit from the retained loyal inframarginal customers and the decrease in profit from the loss of marginal customers. This trade-off could constrain the profitability of the anticompetitive conduct. However, personalised pricing and algorithmic targeting either loosen this constraint, or remove it entirely. Algorithmic targeting also has consequences for the assessment of price-based exclusionary conduct.

First, algorithmic targeting poses a challenge for the relevant price and cost measures used as inputs for the price-cost test. The price-cost test determines whether a dominant firm is charging a below-cost price. Personalised pricing means that there is not a single price prevailing in the market that can be used for the comparison. The relevant price should be for the contestable portion of demand (i.e., the price for marginal customers). Similarly, the cost should be uniquely for the units of output over which the price cuts apply (which may be difficult to identify) (Cheng and Nowag, 2022, pp. 21-27^[58]).

Second, algorithmic targeting raises complex questions regarding the application of the as-efficient competitor test (which is often relied on to assess exclusionary effects in predatory pricing, rebates, and tying and bundling cases). It is unclear how ‘as-efficient’ should be defined in the context of personalised pricing and algorithmic targeting; for example, whether it should apply solely to the production of the individual good or whether it also includes the ability to identify marginal customers, as this will have a significant impact on costs. It may not be reasonable to require a new entrant to be as efficient as the incumbent where the incumbent has developed unique data on customers that facilitates personalised pricing and algorithmic targeting (Cheng and Nowag, 2022, pp. 32-33^[58]).

Once a competition authority has identified harm from a pricing algorithm, there are several remedies an authority could consider. For example, behavioural remedies that could remedy personalised pricing and algorithmic targeting include: (i) limiting the amount of personal data collected by the dominant firm; (ii) the dominant firm sharing the customers’ data with rival firms; (iii) transparency to disclose to users when the dominant firm is implementing a strategy of personalised pricing and what parameters it is taking into consideration; (iv) grant users with a right to opt-out of personalised pricing (Botta and Wiedemann, 2020, pp. 396-397^[36]).

As discussed above, both personalised pricing and algorithmic targeting can in theory facilitate several potential exclusionary harms: (i) predatory pricing; (ii) rebates; and (iii) tying and bundling (Cheng and Nowag, 2022, pp. 7-9^[58]). The following sections detail how algorithmic targeting can make each of these traditional theories of harm more feasible.

Predatory pricing

Depending on the jurisdiction, predatory pricing can either consist of one or two phases. In the US, predatory pricing consists of two phases: (i) a ‘predation phase’ where the dominant firm reduces price below the “*appropriate*” cost measure (which is often an area of dispute (Cheng and Nowag, 2022, pp. 22-

27^[58]) to foreclose a competitor or new entrant, forcing them to exit the market; and (ii) a ‘recoupment phase’ where the dominant firm increases price to at least recover the investment in below-cost prices from the predation phase (Hemphill and Weiser, 2018, p. 2051^[62]). In Europe, proof of recoupment isn’t necessary; proof of predation is sufficient (Cheng and Nowag, 2022, p. 10^[58]).

Algorithms facilitate predatory pricing by allowing firms to both identify and target marginal customers. If a dominant firm can identify marginal customers (i.e., customers at risk of switching), it can target them with below-cost price cuts in the predation phase. A dominant firm can use this predatory pricing to achieve anticompetitive foreclosure of rivals. Algorithmic targeting lowers the cost of predation for the dominant firm, as it avoids losses on inframarginal customers (i.e., customers not at risk of switching). This reduces the need for the dominant firm to recover profits in the recoupment phase, making the overall predatory pricing strategy more feasible (Cheng and Nowag, 2022, pp. 7-8^[58]) (Leslie, 2023^[63]).

Rebates

Rebates are typically either standardised or personalised. Standardised rebates are the same across all customers (e.g., *Post Danmark II*³⁶). Personalised rebates are unique to each customer or transaction (e.g., *Intel*³⁷) (Cheng and Nowag, 2022, p. 8^[58]). However, algorithmic targeting allows a new form of rebate that combines the best elements of standardised rebates, such that it applies to large groups of customers (e.g., larger rebates for marginal customers and lower (or no) rebates for inframarginal customers), and personalised rebates, such that it maximises profits across customers (e.g., by targeting transactions where competition is fiercest) (Cheng and Nowag, 2022, p. 8^[58]).

A dominant firm can use algorithmic targeting to mitigate some of the limitations of standardised rebates (e.g., that they may not be profit maximising for some customers), as well as those of personalised rebates (e.g., offering personalised prices to a large and diverse set of customers may increase transaction costs and undermine profitability) (Cheng and Nowag, 2022, p. 8^[58]). Thus, algorithmic targeting can make it more feasible for a dominant firm to use rebates to prevent customers from switching to a rival resulting in anticompetitive foreclosure of those rivals.

Tying and bundling

A dominant firm can use tying and bundling to leverage its dominance in one market (product A, the tying product, in which the firm is dominant) into another where it is not dominant (product B, the tied product). Tying requires the customer to purchase both the tying and tied products. Bundling dictates how the products are offered by the dominant firm. Bundling can be pure or mixed. Pure bundling means the dominant firm only offers a tied AB bundle, selling product A and B together. Mixed bundling means the dominant firm offers product A and B separately, but also as part of a cheaper tied AB bundle. A dominant firm can use tying and bundling to achieve anticompetitive foreclosure of rivals.

A dominant firm faces a trade-off when deciding whether to provide a tied bundle: (i) the loss of revenue from customers that no longer buy the tying product from the dominant firm because of the tied bundle; and (ii) the gains in revenue from customers that stick with the tied bundle regardless of the tie (Cheng and Nowag, 2022, pp. 8-9^[58]).

Algorithmic targeting allows the dominant firm to offer inframarginal customers (with inelastic demand) solely the tied bundle, which they prefer to purchasing products A and B separately from the dominant firm’s competitors. A dominant firm can then use these additional profits to offer a discounted bundle to marginal customers (with more elastic demand), resulting in the dominant firm offering these customers a lower price than its competitors, ensuring that they do not switch to a competitor. Therefore, algorithmic targeting may lower the degree of market power a dominant firm requires to successfully implement an anticompetitive tying and bundling strategy (Cheng and Nowag, 2022, pp. 29-30^[58]).

3.2.2. Algorithmic exploitative conduct

Exploitative conduct by a dominant firm directly harms consumers through unfair prices or trading conditions (OECD, 2020, p. 50^[18]). Exploitative abuses are rarely prosecuted in most OECD countries, either because they are not contemplated within competition rules (e.g., US, Canada and Mexico) or because they are only very occasionally investigated (e.g., Australia, EU, Japan, Korea and Turkey) (OECD, 2018, p. 27^[3]). The German Bundeskartellamt case against Facebook was the first sanctioned digital exploitative conduct case (Botta and Wiedemann, 2019, p. 465^[64]).³⁸

A dominant firm can use its market power to engage in exploitative conduct such as: (i) excessive pricing (e.g., unfair purchase or selling prices); (ii) unfair trading conditions (e.g., unilaterally imposing other unfair trading conditions); and (iii) price discrimination (e.g., dissimilar conditions to equivalent transactions putting a customer at a competitive disadvantage) (Botta and Wiedemann, 2019, pp. 465-466^[64]). This section first considers excessive pricing and unfair trading conditions, and then discusses price discrimination as an exploitative abuse.

Excessive pricing and unfair trading conditions

A key challenge in exploitative abuse cases is determining whether the conduct is “excessive” or “unfair”. It may be difficult for an authority to determine whether prices or terms are fair, as there is often not a clear benchmark. It is useful to keep in mind that “*exploitative abuses, of which excessive prices are the main example, are extremely rare even in jurisdictions, such as the EU, where competition law allows in principle to investigate them*” (Motta, 2022, p. 16^[60]).

Algorithmic excessive pricing can be both monetary (e.g., using a pricing algorithm) or non-monetary indicators of quality (e.g., using search, recommendation, or allocation algorithms). A dominant firm could use its market power to unilaterally reduce the quality of its algorithm to its own advantage, for example by increasing advertising exposure or worsening data collection terms. Another way to conceptualise this would be as the charging of excessively high non-monetary prices (Gebicka and Heinemann, 2014, p. 165^[65]).

A dominant firm could use self-preferencing to oblige downstream third-party sellers to “*accept unbalanced contractual terms leading to excessive data extraction (favouring future market foreclosure) or wealth transfer (through payments for ancillary services as data analytics or pay for prominence in ranking schemes)*” (Bougette, Budzinski and Marty, 2022, p. 196^[59]). (Hagiu, Teh and Wright, 2022^[66]) consider whether ranking demotion can cause negative welfare effects and find that “*exploitative abuse of third-party margins at the expense of welfare is likely to occur under most self-preferencing scenarios*” (Bougette, Budzinski and Marty, 2022, p. 201^[59]).

In Japan, exploitative abuses can be challenged as an abuse of superior bargaining position (OECD, 2018, p. 28^[3]). The Japan Fair Trade Commission (JFTC) can use the Antimonopoly Act “Abuse of a Superior bargaining position” unfair trade practices to pursue a firm in a superior position (relative to other businesses) that rank demotes customers using its algorithm, putting them at an unfair competitive disadvantage, which forces the customer to accept unfair terms and conditions that benefit the firm (Japan Fair Trade Commission, 2021, p. 38^[9]). The adoption of biased rankings (where fee-paying customers were rank promoted) in search results in a local restaurant website (Kakaku.com) was considered as an “Abuse of a Superior bargaining position”.³⁹

Furthermore, there are examples of biased rankings (by promoting fee-paying third-party products or services in a non-transparent manner) in search results in hotel booking websites in consumer protection cases in the UK⁴⁰ and Australia (see Box 4.1).

Price discrimination

In addition to exclusionary conduct (set out above), pricing algorithms used for personalised pricing or price discrimination can be sanctioned as an exploitative abuse in some jurisdictions. Price discrimination can be an exploitative abuse if it places dissimilar conditions to equivalent transactions putting a customer at a competitive disadvantage.⁴¹ However, these cases are extremely rare.⁴²

The OECD previously provided a step-by-step guide to assess whether personalised pricing is an exploitative abuse (OECD, 2018, p. 30_[3]). This consisted of five steps: (i) identify price differences are not based on costs; (ii) establish that the firm is dominant; (iii) analyse effects on consumer welfare and efficiency to show whether there is evidence of harm; (iv) determine that the harm is persistent and is unlikely to be resolved by the market; and (v) identify the source of discrimination to define the appropriate remedies.

In jurisdictions where price discrimination can be sanctioned as an exploitative abuse, it can nonetheless be difficult to bring these types of cases to court. For example, in the *Serviços de Comunicações e Multimédia SA ('MEO')* case,⁴³ the Court of Justice of the European Union ('CJEU') considered the use of Article 102 TFEU for an exploitative abuse, and showed successful prosecution faces a high burden of proof. It would require a competition authority to prove that: (i) price discrimination is a repeated conduct; (ii) the algorithm systematically discriminates between different groups of consumers (presumably based on an investigation of the underlying algorithm); (iii) that there are no objective justifications for the personalised pricing (e.g., the dominant firm could argue it is optimal pricing that increases overall consumer welfare); and (iv) identify the relevant counterfactual to determine the impact of the personalised pricing on consumer welfare (Botta and Wiedemann, 2020, pp. 392-394, 401_[36]).

Currently no competition authority has sanctioned a case of personalised pricing using Article 102 TFEU, although the likelihood may increase if the adoption of personalised pricing increases as expected (Botta and Wiedemann, 2020, p. 400_[36]).

4 Investigating algorithms

Competition authorities need to be able to identify when algorithms reduce competition. This chapter considers how competition authorities could investigate these algorithmic harms. Specifically, it considers approaches that competition authorities can adopt to investigate algorithms directly, such as algorithmic auditing and explainable AI. It sets out several possible methods and techniques, including the purpose and challenges of each.

In this chapter we consider some of the following questions:

- Is it necessary for a competition authority to investigate an algorithm?
- Is it feasible for competition authorities to investigate an algorithm?
- How can a competition authority investigate an algorithm?
- What specialist skills do competition authorities need to investigate an algorithm?
- How can competition authorities collaborate and learn from others facing similar issues (e.g., other competition authorities, sector regulators, artificial intelligence guidelines)?

4.1. Necessity

As shown in the previous chapter, many concerns arising from extensive use of algorithms are not necessarily novel but can make existing theories of harm more feasible. Authorities then face a challenge due to the level of knowledge and skills they need to understand an algorithm. In some cases, it may not be necessary to develop a deep understanding of the algorithm, for example if it has been used to facilitate a traditional cartel (e.g., UK Trod Ltd/GB Eye Ltd case which relied on explicit agreement between two merchants to not compete on prices).⁴⁴ There may be evidence from internal documents, such as emails or messages, indicating intent to perform the alleged harm. While in other cases, understanding the algorithm may be unavoidable to assess whether there has been any harm (e.g., unilateral harm in the AGCM's Amazon FBA case or EC's Amazon Buy Box case). Therefore, it seems inevitable that authorities will increasingly be faced with cases that require an understanding of algorithms, and thus will need specialist staff with expertise in computer and/or data science.

How competition authorities could investigate algorithmic harms was touched on during the OECD roundtable on *Algorithms and Collusion* in June 2017. As set out in (Gal, 2017, pp. 5-7^[67]), competition authorities and regulatory agencies can try to understand which features the algorithm used in its decision-making process, and then an authority could then use this information to forbid the use of certain features to remedy a harm. The discussion also raised the benefit of including data scientists in the investigation process to provide technological insight into algorithms and algorithmic solutions (OECD, 2017, p. 9^[68]). Competition authorities have been considering this further in recent years as they are faced with more cases involving algorithms, and in some instances, expanded responsibilities to enforce ex-ante digital regulation.

Some authors believe there is a need for competition authorities to investigate algorithms directly, particularly considering recent abuse of dominance decisions in digital cases in Europe (Caffarra, 2021, p. 7^[69]). Competition authorities and governments seem to have acknowledged the need to develop the

knowledge, skills and access required to investigate these algorithmic harms. This is both in terms of the creation of new digital units (see Table 4.3 below) and in terms of the data gathering powers in new ex-ante digital regulations that are coming into force (such as the EU's Digital Markets Act⁴⁵ and the UK's Digital Markets Unit⁴⁶).

4.2. Feasibility

There is a concern that it may not be possible to understand the decision-making process of some algorithms, particularly the most complex machine learning or deep learning models. These algorithms are often referred to as “black boxes” given the lack of transparency regarding the decision-making process they use to go from an input to the output. However, there is a spectrum of complexity, and algorithms may pose different levels of difficulty for competition authorities.⁴⁷ Some algorithmic harms will be harder to identify than others. For example, it may be possible to identify aggregate harm from algorithmic collusion, such as a general increase in prices, but difficult to understand which specific algorithms, and the interactions between them, were responsible for this general price increase, particularly in a situation where all firms are using algorithms that adjust prices based on competitor prices and general market conditions (Competition & Markets Authority, 2021, p. 36^[5]). The developing fields of explainable AI and algorithmic auditing offer scope to understand the functioning of algorithms.

Explainable AI is a field concerned with the development of methods that explain and interpret machine learning models (Linardatos, Papastefanopoulos and Kotsiantis, 2020^[70]).⁴⁸ Explainable AI broadly suggests two potential approaches to enable humans to understand algorithmic decision-making: (i) adopt inherently interpretable algorithms (known as “white box” algorithms); or (ii) use backward engineering methods (also known as post-hoc methods) (Deng, 2020, pp. 979-980^[42]). Current explainable AI methods may be more suited to explaining decision-making by an individual algorithm. Unless an algorithm is explicitly coded to collude, it may be difficult to identify algorithmic collusion just by examining the algorithm (Van Uytsel, 2018, pp. 175-176^[41]). Thus, these methods may be better to identify unilateral conduct rather than algorithmic collusion (although some authorities consider it is already possible⁴⁹ and more research may be conducted in this area in future) (Deng, 2020, p. 1018^[42]).

Algorithmic auditing⁵⁰ can refer to a variety of methods to review algorithms. It can be used for regulatory inspection to determine whether an algorithm is compliant with a law, regulation or norm, where regulators or auditing professionals can use a variety of tools or methods (Ada Lovelace Institute, 2020, p. 3^[71]). In recent years, several competition authorities have published policy papers in which they consider how they could investigate algorithms, either by auditing the algorithm directly or by auditing the data used by the algorithm. These competition authority reports explain that there are several possible ways that they can investigate an algorithm. Code review is just one of several possible approaches. The scope of the investigation, and precisely what it involves, will vary on a case-by-case basis (see section 4.3 below for more details).

While certain methods may not always be feasible given the complexity of the algorithm, there are now several cases where competition and consumer authorities have considered the functioning of more complex algorithms. For example, the Australian Competition and Consumer Commission's ('ACCC') Trivago case (see Box 4.1). While this was a consumer protection case, it provides an example of an authority successfully investigating an algorithm. Even though machine learning models are sometimes treated as a 'black box' (particularly if they have been 'trained' on a particular dataset or learn through trial and error) and some machine learning models are more interpretable than others, this case shows that the authority can benefit from investigating the algorithm directly. Furthermore, in the Japan Fair Trade Commission (JFTC) Kakaku.com case the court requested that the website disclose part of its algorithms.⁵¹

Box 4.1. ACCC vs Trivago case study

Trivago N.V. is an online search and price comparison platform for travel accommodation. The ACCC brought a consumer protection case against Trivago in the case “Australian Competition and Consumer Commission v Trivago N.V. [2020] FCA 16”. Much of the analytical work on this case involved understanding Trivago’s algorithm.

This was a consumer protection, not competition, case. The ACCC alleged that Trivago had misled consumers. Trivago had television advertisements that stated the Trivago platform would enable the user “to find the ideal hotel for the best price”. The Trivago website presented prices from several different online booking sites for a particular hotel, where one of the prices appeared in a prominent position (in large green font surrounded by white space), known as the “Top Position Offer”. The case focused on how the “Top Position Offer” was selected and whether it was indeed the lowest available price. Ultimately, the expert evidence at trial found that in approximately 66% of listings, the “Top Position Offer” was not the lowest available price.

In August 2018 the ACCC initiated proceedings against Trivago and in January 2020, the Federal Court found Trivago had breached the Australian Consumer Law when it made misleading representations about hotel room rates on its website and television advertising. In March 2020, Trivago appealed the Court’s decision. This was dismissed by the Full Federal Court in November 2020. Trivago was ultimately fined AUD 44.7 million.

This case shows that competition authorities can investigate algorithms. Often machine learning models are treated as a ‘black box’. This is because the model has often been ‘trained’ on a particular dataset or learns through trial and error. However, this case shows that this doesn’t mean there is nothing that can be learned from investigating an algorithm (although some machine learning models are more interpretable than others). Some examples of model-agnostic methods of interpretability are: (i) partial dependence plots; (ii) accumulated local effects; (iii) local interpretable model-agnostic explanations; and (iv) Shapley additive explanations.

Data scientists played an important role in the case. ACCC data scientists were involved in the case from the beginning to end. They initially formed the information requests to obtain input and output data as well as the source code itself, which the ACCC could get using its compulsory information gathering powers. The ACCC data scientists reviewed the code line-by-line and performed some descriptive statistics to help the investigation team analyse the algorithm, which was resource-intensive, but worthwhile. They formed an initial assessment that there was merit in the case and proceedings were commenced. Both the ACCC and Trivago hired an independent expert. The ACCC data scientists helped determine the questions for the experts and assisted the investigation team with interpreting the expert evidence.

Both Trivago and the ACCC hired technical experts. The two experts used different methodologies to determine which inputs were most influential in the algorithm and came to different conclusions. The experts often used analogies to try to explain these differences to the court. However, the experts could agree that that in 66% of listings, the Top Position Offer was not the lowest available price in the listing. So even when dealing with a complex algorithm, regardless of the various available methods of interpretability, sometimes a simple descriptive statistic can succinctly provide a clear message.

Source: Australian Federal Court Judgment: <https://www.judgments.fedcourt.gov.au/judgments/Judgments/fca/single/2020/2020fca0016>
Presentation of the case by Sally Foskett (Executive Director, Data Strategy, ACCC): <https://www.youtube.com/watch?v=FEN0-fEKbGQ>

4.3. Investigation techniques

To date, there is not a single all-embracing centralised framework for analysing algorithms that brings together all relevant standards and guidelines (Oosterwijk, Pirkovski and Zielman, 2022, p. 90^[72]). Algorithms differ in complexity. The sophistication of AI algorithms can range from simple algorithms, such as decision trees (that apply ‘if, then...’ rules), to more sophisticated algorithms, such as neural networks (Oosterwijk, Pirkovski and Zielman, 2022, p. 91^[72]). Therefore, the degree to which an authority can determine the working of an algorithm will depend on its complexity.

There are three main sources that detail how competition authorities have investigated (or could investigate) algorithms in practice. First, several competition authorities have published reports outlining how they could investigate a firm’s algorithms. Second, decisions for competition authority cases involving algorithms provide insight into what the authority has gleaned from the investigation regarding the functioning of the algorithm. Many relevant parts of these decisions are redacted (given the functioning of the algorithm can be proprietary information). Nonetheless, these decisions suggest that the authority has investigated the algorithm directly and understand the key attributes driving its decision-making process. Third, there is an academic literature regarding algorithmic auditing and explainable AI that provides methods and approaches to understand and review algorithms. Some of the key messages from these various sources are set out below.

Several competition authorities have published reports outlining how they could investigate a firm’s algorithms in practice. These papers include studies by the UK (Competition & Markets Authority, 2021, pp. 35-44^[5]), Japan (Japan Fair Trade Commission, 2021, p. 38^[9]), the Netherlands (Authority for Consumers and Markets, 2020, pp. 8-13^[12]), and a joint report by France and Germany (Autorité de la concurrence & Bundeskartellamt, 2019, pp. 61-74^[14]). Other regulators have also set out guidance regarding how to understand algorithms (e.g., (ICO, 2020^[73])). These reports provide firms with a view of what they can expect from an investigation. They broadly consider: (i) investigating the functioning and behaviour of an algorithm without access to the algorithm and data; (ii) investigation powers; (iii) investigating the role of an algorithm; (iv) investigating the functioning and behaviour of an algorithm with access to the algorithm and data; and (v) challenges and other important considerations. This section considers each of these elements in turn.

Investigating the functioning and behaviour of the algorithm is potentially possible without access to the algorithm and/or underlying data (Competition & Markets Authority, 2021, pp. 35-39^[5]). An authority could use these methods both before and/or during a formal investigation. However, these techniques are usually less effective than those when the algorithm and data are accessible. These techniques are largely based on the academic literature on algorithmic auditing and explainable AI.

Algorithmic auditing has been around for over a decade and much of these studies were predominantly motivated by a desire for social justice, where researchers or activists were responding to public demand to investigate algorithms that increasingly make important (but opaque) decisions (Vecchione, Levy and Barocas, 2021^[74]). Cathy O’Neil further popularised the concept of algorithmic auditing in her book “Weapons of Math Destruction” (O’Neil, 2016^[75]). She set out several ways in which algorithms can harm citizens and called on regulators to intervene to address these harms.⁵² She outlined how algorithmic auditing can unveil the objective, workings and outcomes of these potentially harmful algorithms.

Algorithmic auditing can refer to a variety of methods to review algorithms (both with and without access to the source code and data). These methods can take different forms, such as reviewing governance and technical documentation, testing an algorithm’s outputs, or inspecting its inner workings (Digital Regulation Cooperation Forum, 2022, p. 2^[76]). The academic literature has set out several possible approaches to algorithm audits: code audit, user survey, scraping audit, API audit, sock-puppet audit, and crowd-sourced audit (Sandvig et al., 2014^[77]) (Ada Lovelace Institute, 2021^[78]). Source code sometimes provides a firm with a competitive edge, and can be confidential commercial information, although this is not always the

case.⁵³ Twitter recently took legal action to demand GitHub, a code-sharing service, to identify who publicly posted part of Twitter’s source code on GitHub.⁵⁴ Thus, excluding code audit, most of the academic algorithmic auditing literature considers methods that do not rely on the underlying source code (Metaxa et al., 2021, p. 277^[79]). For example, there are several examples of algorithmic auditing academic papers investigating the use of personalisation and pricing.⁵⁵ The techniques that an authority can perform without access to the algorithm and data are summarised in Table 4.1 below.

Table 4.1. Algorithm auditing techniques without access to the algorithm and data

Audit method	Description	Purpose	Challenges
User survey	Auditors conduct a survey and/or perform user interviews, to gather descriptive data of user experience on the platform.	Gathering information about user experience on a platform – to paint a rough picture of the types of problematic behaviour that could then be further investigated.	Vulnerable to common social science concerns with surveys – pressure to answer in a particular way, unreliable human memory and difficulty to attribute causation to findings.
Scraping audit	Auditors collect data directly from a platform, typically by writing code to automatically click or scroll through a webpage to collect data of interest (for instance, text that users post).	Understanding content as presented on the platform – particularly making descriptive statements (e.g. ‘this proportion of search results contained this term’) or comparing results for different groups or terms.	Requires the development of a custom tool for each digital platform, which can be brittle as small (legitimate) changes to a website’s layout can break the program.
API audit	Auditors access data through a programmatic interface provided by the platform that allows them to write computer programs to send and receive information to/from a platform, e.g. an API might allow a user to send a search term and get back the number of posts matching that search term.	Easier programmatic access to data than a scraping audit – allowing easier automation of collection for descriptive statements or comparative work.	Publicly available APIs may not provide a regulator with the data they need. With information-gathering powers, they could compel a platform to provide access to further APIs or even a custom API, but this may require additional engineering work by platforms.
Sock-puppet audit	Auditors use computer programs to impersonate users on the platform (these programs are called ‘sock puppets’). The data generated by the platform in response to the programmed users is recorded and analysed.	Understanding what a particular user profile, or set of user profiles, may experience on a platform.	Sock puppets are only impersonating users – they aren’t real users and so are at best a proxy for individual user activity and experience.
Crowd-sourced audit	A crowd-sourced audit (sometimes known as ‘mystery shopper’) uses real users who collect information from the platform while they are using it – either by manually reporting experience or through automated means like a browser extension.	Observing what content users are experiencing on a platform and whether different profiles of users are experiencing different content.	Requires custom data-collection approach for each media platform being audited, often relying on web-scraping techniques; so far only demonstrated on desktop not mobile devices so may skew results or overlook mobile experiences.

Source: This table is taken from (Ada Lovelace Institute, 2021, pp. 13-14^[78]) and is based on the article (Sandvig et al., 2014^[77]).

Once a harm is suspected, a competition authority can launch an investigation and use their standard investigation powers to investigate an algorithm (Authority for Consumers and Markets, 2020, p. 8^[12]) (Autorité de la concurrence & Bundeskartellamt, 2019, pp. 65-67^[14]). The relevant investigation powers include dawn raids, requests for information and/ or interviews (e.g., with the firm’s software engineers who developed the algorithm). These would aim to obtain any relevant code, data or documentation.

Depending on the jurisdiction, this could also extend to third parties when an algorithm is developed and maintained externally by said third parties.

Once an investigation has been launched, before jumping into technical aspects of investigating the algorithm, the authority can start to investigate the role of the algorithm to provide context to its use (Authority for Consumers and Markets, 2020, pp. 9-10_[12]) (Autorité de la concurrence & Bundeskartellamt, 2019, pp. 62-64_[14]). An investigation of the role of the algorithm (procedural transparency) elucidates the purpose/objective of the algorithm within the context of the business, the underlying assumptions and input/output data, the roles of people that developed the algorithm (including any third-party contractual terms), and whether any risks were identified in its development (including test or debugging reports) as well as how they have been addressed.

Investigating the functioning and behaviour of the algorithm is usually more effective with access to the algorithm and/or underlying data (Authority for Consumers and Markets, 2020, pp. 10-12_[12]) (Autorité de la concurrence & Bundeskartellamt, 2019, pp. 67-74_[14]) (Competition & Markets Authority, 2021, pp. 39-42_[5]). Again, these techniques are largely based on the algorithmic auditing and explainable AI literature. As stated above, given the secrecy surrounding some platform algorithms, the adoption of code review in the algorithmic auditing literature remains relatively under-explored and could be ripe for future research (Bandy, 2021, p. 26_[80]). Table 4.2 details at a high level some techniques that competition authorities can pursue with access to the algorithm and/or data. These consist of static and dynamic techniques.

Explainable AI involves the adoption of AI methods to make complex algorithms more transparent, interpretable, and explainable. These techniques often use an algorithm to fully explain, or approximate, the functioning of the algorithm under investigation. Again, this literature has developed from user's need to be able to trust AI models and predictions (Ribeiro, Singh and Guestrin, 2016_[81]). While there has been progress to develop methods to explain some of the most complex AI approaches, such as deep neural networks (Samek, Wiegand and Müller, 2017_[82]) (Montavon, Samek and Müller, 2018_[83]), it remains challenging (Gilpin et al., 2018_[84]). A recent paper outlines some of the main approaches adopted in industry and the academic literature (such as Local Interpretable Model-agnostic Explanations ('LIME')⁵⁶, Anchors⁵⁷ and Mechanistic Interpretability⁵⁸) but reiterates that there remains no concrete way of completely understanding the most complex models, such as deep neural networks (Dwivedi et al., 2023_[85]).

Investigating the surrounding documentation and context of the algorithm, as well as uncovering the role of the algorithm (as explained above), can also provide insight regarding the algorithm's behaviour. These methods can include reviewing the documentation, pseudocode (which describes the steps in an algorithm) and any general explanations of the algorithm. It could also consider the whole life cycle of the algorithm (which could include the conception of the system, commission, design, development, deployment, ongoing use, subsequent assessments of its functions). And finally, interviewing staff (such as research engineers) and product teams can also shed light on the functioning and behaviour of the algorithm.

Authorities can also consider other testing methods, such as randomised control trials (RCT) or A/B testing, which are not captured within the concept of algorithm auditing (Metaxa et al., 2021, pp. 277-278_[79]). Large digital companies typically consider these methods on a systematic basis for their own internal purposes. Thus, an authority can look at historical studies. Or the firm under investigation may be able to help the authority implement RCT or A/B that would be relevant for the investigation.⁵⁹

There have now been several cases in which an authority has had access to the algorithm and data. The ACCC's Trivago case (see Box 4.1) provides an example of manual code review by data scientists. While the Italian AGCM considered how Amazon created a Featured Merchant Algorithm ('FMA') score (seemingly using a linear function of five variables, estimated using econometric or machine learning approaches) to determine which offer would be included in the Amazon Buy Box (AGCM, 2021, pp. 78-79_[86]).⁶⁰ Finally, the European Commission considered the following evidence in the Google Shopping

case: “1) contemporary documents from both Google and other market players; 2) very significant quantities of real-world data including 5.2 Terabytes of actual search results from Google (around 1.7 billion search queries); 3) experiments and surveys, analysing in particular the impact of visibility in search results on consumer behaviour and click-through rates; 4) financial and traffic data which outline the commercial importance of visibility in Google’s search results and the impact of being demoted; and 5) an extensive market investigation of customers and competitors in the markets concerned (the Commission addressed questionnaires to several hundred companies)”⁶¹

Table 4.2. Algorithm auditing techniques with access to the algorithm and/or data

Audit method	Description	Purpose	Challenges
Static techniques (such as manual code review or static analysis)	Auditors have direct access to the codebase of the underlying system, or ‘pseudocode’ plain-English descriptions of what the code does. Static analysis can run the code in isolation from its environment.	Understanding intentions of the algorithm and how it works (e.g., nature of the input and output data, the structure of the code, indications of how the code may behave based on certain inputs); in the case of machine learning, useful for understanding which objectives are being optimised.	Some major limitations. Code can be complicated or obfuscated. Static methods, on their own, say nothing about how a program interacts with its environment. Hard to see effects/outcomes through code. Can lead to incomplete or incorrect conclusions. Extremely challenging for complex algorithmic software.
Dynamic techniques	Automated testing through execution of the code (i.e., run the program and assess the outputs for particular inputs or the state of the program as it is running)	By running a program, dynamic testing can provide insights not available through static source code review.	Dynamic methods are limited by the finite number of inputs that can be tested or outputs that can be observed. Dynamic methods also require full control of the algorithm or the ability to mandate the firm to run the relevant tests.
<i>Dynamic techniques: Black-box testing</i>	<i>“Black box testing” considers only the inputs and outputs of a system or component.</i>	<i>Observational method in which an analyst can see how the program runs in the field with its natural inputs.</i>	<i>Tells an analyst very little about why differential behavior was observed.</i>
<i>Dynamic techniques: White-box testing</i>	<i>“White-box testing” in which the structure of the system’s internals is used to design test cases.</i>	<i>Testing method, which is more powerful than black-box testing, where an analyst chooses inputs and submits them to the program. Allows an analyst to monitor deviations from expected behavior (e.g., unforeseen bugs, security compromise, abuse, and other unexpected behavior).</i>	<i>Cannot provide complete coverage of a program’s behavior, as it explains little about what happens to inputs which have not been tested, even those that differ very slightly.</i>

Note: Italics indicate that the row is a subset of the approach set out directly above (i.e., black-box testing and white-box testing are both types of dynamic technique).

Source: Based on input from (Kroll et al., 2017^[87]), (Competition & Markets Authority, 2021^[53]) and (Ada Lovelace Institute, 2021, pp. 13-14^[78])

Despite the several avenues through which competition authorities can investigate algorithms, it is complex and difficult work, with several challenges and additional things that authorities need to consider (Authority for Consumers and Markets, 2020, pp. 12-13^[12]) (Competition & Markets Authority, 2021, pp. 10-12^[53]).

First, several of the methods outlined above can be time-consuming and costly to implement and may not provide sufficient proof of harm (such as manual code review, where the code is particularly complicated, or the harmful effects of the algorithm depend on the input data or general environment in which the algorithm operates). This may be particularly the case for complex machine-learning algorithms that are transient (i.e., they are constantly evolving based on the training data and developments to the algorithm). Therefore, investigations need to be proportionate to the harm being investigated and performed at the appropriate level of detail. For example, user surveys (see Table 4.1) may be too superficial while dynamic techniques (see Table 4.2) may be too granular.

Second, a firm often employs several algorithms together in a wider system which can make understanding the interaction between these algorithms difficult. Third, these wider systems of algorithms often include an element of human judgement (either from employees or consumers) which can make it harder to understand the overall behaviour of the algorithmic system. Fourth, algorithms are often the foundation of value of a digital firm. Therefore, any investigation will need to consider that the confidentiality of the algorithm is maintained, and trade secrets are kept from competitors. An authority may also face issues regarding privacy and user security. Finally, if the firm operates across international borders or uses algorithms that have been developed by third parties, this may entail further complications for an authority when gathering evidence.

4.4. Specialist skills

The techniques to investigate the functioning and behaviour of an algorithm can be complex and technical. Therefore, competition authorities usually need a wider skill and knowledge base to investigate algorithmic theories of harm. Several competition authorities have already started this process (Schrepel and Groza, 2022^[88]). Many have set up data units, hiring data scientists and technologists to assist them with their market investigations, merger control, enforcement cases, and in some jurisdictions, to implement new digital regulation (OECD, 2022, p. 9^[89]). Competition authorities are also using these skills to reverse-engineer and understand companies' algorithms (Lorenzoni, 2022, pp. 44-46^[90]). By the end of 2019, 11 of 35 surveyed competition authorities had a data unit.⁶² This had increased to 19 of 32 surveyed competition authorities in 2022.⁶³

Table 4.3 shows the percentage of non-administrative competition staff who are data scientists for the 19 competition authorities that indicated they had a data unit in 2022. While still a relatively small share of staff, the number of data scientists at several authorities is relatively large given many data units have only been established in the last few years. For example, the UK CMA created a data unit in February 2019 (Competition & Markets Authority, 2022, p. 4^[91]). Data scientists at authorities likely work on a range of workstreams, not exclusively those related to cases involving algorithms, nonetheless they are indicative of competition authorities investing in the relevant expertise to pursue these kinds of cases.

Given a range of regulators will also require these skills, a centralised expert body could be a potential solution to pool resources (Coglianese, 2023^[92]). For example, the Singapore government has a central team of data scientists and software engineers that support departments across government.⁶⁴ Furthermore, competition authorities can engage with other authorities globally to share expertise and knowledge, for example at national competition authority conferences,⁶⁵ and through international channels.⁶⁶ They should also engage with developments in academia and could consider using third-party for-profit algorithmic auditing companies⁶⁷ where appropriate (Ada Lovelace Institute, 2021, p. 49^[78]). For example, the UK government considers that the emerging market for AI assurance will play an important role in helping firms to understand whether their AI algorithms meet regulatory requirements (UK Department for Science, Innovation & Technology, 2023, p. 64^[93]).

Table 4.3. Data scientists at competition authorities that have data units

Agency	Percentage of non-administrative competition staff who are data scientists
Australia's Competition and Consumer Commission	N/A ¹
Austria's Federal Competition Authority	6% ²
Brazil's Administrative Council for Economic Defence	0%
Canada's Competition Bureau	N/A
Chile's National Economic Prosecutor	3%
Colombia's Superintendence of Industry and Commerce	2%
European Union's Directorate-General for Competition ³	5%
France's Competition Authority	1%
Germany's Federal Cartel Office	N/A ⁴
Greece's Competition Commission	5%
Korea's Fair Trade Commission	4%
Mexico's Federal Economic Competition Commission	6% ⁵
Netherlands' Authority for Consumers	3%
New Zealand's Commerce Commission	0%
Poland's Office of Competition and Consumer Protection	12%
Romania's Competition Council ⁶	6%
Spain's National Commission of Markets and Competition	3%
Switzerland's Competition Commission	0%
United Kingdom's Competition and Markets Authority	6%

Notes:

¹ N/A because staff from the ACCC's Strategic Data Analysis Unit work on a pro rata basis as data scientists at the ACCC.

² IT forensic staff.

³ There is not a specific "data unit", although there are a number of separate teams supporting competition investigations from a data analytics point of view. In particular, Unit COMP.DDG1.02 Intelligence, Analysis and Forensic IT Support pools professional enforcers specialised in economic and financial investigations, intelligence analysis, data science and IT security. Unit COMP I.3 Digital Business Solutions develops and operates digital solutions to support investigation work (including eDiscovery) and provides advanced data services for investigations whose requirements are not met by standard solutions. In this context, Unit COMP I.3 conducts research on advanced data technologies.

⁴ N/A because staff roles may overlap in certain areas.

⁵ Data scientists may also be lawyers or economists.

⁶ The Information Technology Unit is part of the research directorate.

Source: GCR Rating Enforcement 2022, here: <https://globalcompetitionreview.com/survey/rating-enforcement/2022>

4.5. Coordination and collaboration

Artificial intelligence is being adopted in many parts of the economy and is thus under review across several regulatory authorities, resulting in a significant coordination problem (Marchant, 2023^[94]). Domain-specific knowledge (e.g., competition policy, financial markets, healthcare) means that it may not make sense to have a single regulator for artificial intelligence that could regulate all the problematic aspects of machine learning (Coglianese, 2023^[92]). There are two types of legal framework emerging for AI: (i) hard law measures (e.g., the EU AI Act); and (ii) soft law measures (e.g., OECD AI guidelines) (Larsen and Yu, 2023^[95]). Therefore, governments and policymakers will need to coordinate their response to the risks posed by AI.

Competition authorities can also learn from each other and benefit from collaboration. Most large digital firms have an international cross-border reach. Competition authorities around the world are grappling with similar issues to address these harms. Therefore, it is important that competition authorities work together (Japan Fair Trade Commission, 2021, p. 40^[9]). Authorities can also benefit from sharing experience and expertise, for example through workshops and roundtables at the OECD and working groups at the ICN.⁶⁸

There are also examples of jurisdictions developing bilateral relationships (Competition & Markets Authority, 2021, p. 11^[28]). Furthermore, firms sometimes offer to implement commitments globally (not just in the jurisdiction in which a competition law infringement was found) benefiting consumers around the world. For example, Google offered global commitments in the France Autorité de la Concurrence online advertising case⁶⁹ and the UK Competition and Markets Authority privacy sandbox case.⁷⁰

Competition authorities can also learn from other sector regulators that have faced similar issues. Several jurisdictions are adopting coordinated digital regulation across several sector regulators, such as Australia⁷¹, the Netherlands⁷², and the UK⁷³. This highlights the importance of sector regulators “*sharing expertise, developing common capabilities, maximising efficiencies in the way regulators operate, and minimising unnecessary burdens on business will be paramount*”.⁷⁴ For example, the UK Digital Regulation Cooperation Forum (DRCF) aims to collaborate to support improvements in algorithmic transparency by improving UK sector regulator capabilities for algorithmic auditing, researching the market for third-party auditing, and promoting transparency in algorithmic procurement.⁷⁵ The UK government expects regulators to proactively collaborate on implementing the principles in the recently proposed pro-innovation regulatory framework for AI (UK Department for Science, Innovation & Technology, 2023, p. 40^[93]).

The UK Financial Conduct Authority (FCA) have conducted research into algorithmic explainability.⁷⁶ They discuss two main approaches: (a) 'interpretability by design' and (b) 'reverse engineering explanatory features'. The former requires building a simpler algorithm at the outset, but this may come at the price of predictive capability. The latter uses a second separate algorithm that provides a simplified way of interpreting a black box machine learning algorithm.

Financial regulators, such as the FCA, have been faced with issues of algorithmic trading for years. The UK FCA's review of algorithmic trading compliance in wholesale markets, which reviews firms across the market, provides examples of good and bad practice.⁷⁷ The OECD has also acknowledged the increasing use of artificial intelligence, machine learning and algorithms in financial services with revisions to the Principles on Financial Consumer Protection.⁷⁸

Other sector regulators often use regulatory sandboxes, with several examples across the OECD. “*A regulatory sandbox refers to a limited form of regulatory waiver or flexibility for firms, enabling them to test new business models with reduced regulatory requirements. Sandboxes often include mechanisms intended to ensure overarching regulatory objectives, including consumer protection. Regulatory sandboxes are typically organised and administered on a case-by-case basis by the relevant regulatory authorities. Regulatory sandboxes have emerged in a range of sectors across the OECD and beyond, notably in finance but also in health, transport, legal services, aviation and energy*” (OECD, 2020^[96]). The UK Financial Conduct Authority and the Hellenic Competition Commission have regulatory sandboxes (see Box 4.2). Furthermore, jurisdictions that are implementing ex-ante digital regulation could consider the use of regulatory sandboxes as a means for firms to test their algorithms and address any potential harms in a safe regulatory space (Competition & Markets Authority, 2021, p. 49^[53]). Although, as noted above, regulatory sandboxes may be more appropriate to identify algorithmic unilateral harms than algorithmic coordinated harms (Van Uytsel, 2018, pp. 175-178^[41]).

Competition authorities can also learn from the AI soft law measures. There is not yet hard law (i.e., that is binding on the parties and can be enforced before a court) governing AI. There is currently mostly soft law (i.e., agreements, principles or declarations that are not legally binding).⁷⁹ The OECD AI Principles are an example of soft law and were the first set of international principles guiding AI (see Box 4.3), which the OECD helps governments to implement through the OECD Working Party on Artificial Intelligence Governance (AIGO).⁸⁰ The OECD AI principles were developed with engagement from civil society as well as industry (e.g., (Facebook, 2021, pp. 13-14^[97])). However, the EU AI Act is likely to be the first hard law governing AI by any major regulator globally.⁸¹ The EU AI Act sets out what an AI auditing ecosystem could look like (Larsen and Yu, 2023^[95]).⁸² Given the ongoing rapid advancements in AI, there are likely to be relatively fast and evolving policy responses from governments around the world.

Box 4.2. Examples of regulatory sandboxes

Financial Conduct Authority, Regulatory Sandbox, United Kingdom

On 9 May 2016, the UK Financial Conduct Authority ('FCA') launched its regulatory sandbox. The sandbox is a 'safe space' with regulatory oversight that allows firms to test new innovative propositions in the live market with real consumers. It is always open for applications. It is reported that 92% of firms who have used the Regulatory Sandbox go on to become successfully authorised. Over 800 businesses have used the FCA's Regulatory Sandbox, which has allowed them to reach market on average 40% faster. Furthermore, participation has been particularly financially beneficial for smaller firms.

The benefits of the regulatory sandbox for firms are: (i) the ability to test products and services in a controlled environment; (ii) the opportunity to find out whether a business model is attractive to consumers, or how a particular technology works in the market; (iii) a reduced time to market at potentially lower cost; and (iv) support in identifying consumer protection safeguards that can be built into new products and services.

The benefits of regulatory sandboxes for regulators are: (i) getting innovative products and services to market faster to the benefit of consumers; (ii) identify any unnecessary regulatory barriers to innovation; (iii) identify emerging technology and markets where regulation may need to adapt.

Source : <https://www.fca.org.uk/firms/innovation/regulatory-sandbox>; <https://www.fca.org.uk/news/speeches/innovation-regulation-partners-success-financial-services>; <https://www.fca.org.uk/news/press-releases/financial-conduct-authority%E2%80%99s-regulatory-sandbox-opens-applications>; (UK Department for Science, Innovation & Technology, 2023, p. 60^[93])

Hellenic Competition Commission, Sustainability Sandbox, Greece

On 3 October 2022, the Hellenic Competition Commission (HCC) officially launched its regulatory sandbox for sustainability issues. The aim of the sandbox is to create a supervised space to attract innovative business proposals that contribute to sustainable development. The HCC will apply several evaluation criteria that will enable them to assess whether specific business plans/models raise competition concerns. The HCC will consider: (i) the existing competition law framework (including the relevant case law for considering broader public interest reasons); and (ii) key performance indicators ('KPIs') related to sustainable development.

The regulatory sandbox will mainly consider multilateral behaviour (agreement, decision, etc.), either between competitors (horizontal) or within a supply chain (vertical). However, in a minority of cases, it may also concern unilateral behaviour. The HCC will initially focus on specific industries, such as energy, recycling/waste management, industrial production of consumer products, production and/or distribution of food, pharmaceuticals, healthcare, etc.

Source: <https://www.epant.gr/en/enimerosi/sandbox.html>; <https://sandbox.epant.gr/en/sandbox-sustainable-development/>

Box 4.3. OECD AI Principles – Recommendation of the Council on Artificial Intelligence

The Recommendation on Artificial Intelligence (AI) – the first intergovernmental standard on AI – was adopted by the OECD Council at Ministerial level on 22 May 2019 on the proposal of the Committee on Digital Economy Policy (CDEP). The Recommendation identifies five complementary values-based principles for the responsible stewardship of trustworthy AI.

1. Inclusive growth, sustainable development and well-being

Stakeholders should proactively engage in responsible stewardship of trustworthy AI in pursuit of beneficial outcomes for people and the planet, such as augmenting human capabilities and enhancing creativity, advancing inclusion of underrepresented populations, reducing economic, social, gender and other inequalities, and protecting natural environments, thus invigorating inclusive growth, sustainable development and well-being.

2. Human-centred values and fairness

a) AI actors should respect the rule of law, human rights and democratic values, throughout the AI system lifecycle. These include freedom, dignity and autonomy, privacy and data protection, non-discrimination and equality, diversity, fairness, social justice, and internationally recognised labour rights.

b) To this end, AI actors should implement mechanisms and safeguards, such as capacity for human determination, that are appropriate to the context and consistent with the state of art.

3. Transparency and explainability

AI Actors should commit to transparency and responsible disclosure regarding AI systems. To this end, they should provide meaningful information, appropriate to the context, and consistent with the state of art:

- i. to foster a general understanding of AI systems,
- ii. to make stakeholders aware of their interactions with AI systems, including in the workplace,
- iii. to enable those affected by an AI system to understand the outcome, and,
- iv. to enable those adversely affected by an AI system to challenge its outcome based on plain and easy-to-understand information on the factors, and the logic that served as the basis for the prediction, recommendation or decision.

4. Robustness, security and safety

a) AI systems should be robust, secure and safe throughout their entire lifecycle so that, in conditions of normal use, foreseeable use or misuse, or other adverse conditions, they function appropriately and do not pose unreasonable safety risk.

b) To this end, AI actors should ensure traceability, including in relation to datasets, processes and decisions made during the AI system lifecycle, to enable analysis of the AI system's outcomes and responses to inquiry, appropriate to the context and consistent with the state of art.

c) AI actors should, based on their roles, the context, and their ability to act, apply a systematic risk management approach to each phase of the AI system lifecycle on a continuous basis to address risks related to AI systems, including privacy, digital security, safety and bias.

5. Accountability

AI actors should be accountable for the proper functioning of AI systems and for the respect of the above principles, based on their roles, the context, and consistent with the state of art.

Source: (OECD, 2022^[98]) OECD (2022) Recommendation of the Council on Artificial Intelligence <https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449>; and OECD AI Principles Overview <https://oecd.ai/en/ai-principles>

5 Conclusion

Algorithms and AI are increasingly permeating our lives and improving our living standards. While monitoring and dynamic pricing algorithms are becoming increasingly common in online markets, there still seems to be relatively limited evidence of widespread adoption of personalised pricing. Other algorithms, such as search and recommendation algorithms, have created new markets and disrupted existing ones. While already common in online markets, algorithms are also becoming more prevalent in offline markets. Algorithms can be efficiency-enhancing and pro-competitive. For example, they can contribute to new and better products, lower production costs, lower barriers to entry, lower search costs, and better balance between supply and demand.

However, firms can also use algorithms in ways that reduce competition and harm consumers. This includes co-ordinated conduct, through algorithmic collusion, but also unilateral conduct that can exclude competitors and exploit consumers directly. Algorithmic exclusionary harms include self-preferencing, predatory pricing, rebates and tying and bundling. Algorithmic exploitative harm can pertain to excessive pricing, unfair trading terms and price discrimination. While there are still relatively few cases, the increasing prevalence of algorithms, means that competition authorities should remain vigilant. As regards algorithmic collusion, competition authorities can identify markets where multiple firms use pricing algorithms provided by the same third-party, as these markets could be particularly susceptible to inflated prices.

There is an ongoing debate as to whether existing competition law is sufficient to address these algorithmic harms. One of the main unresolved issues is whether algorithmic autonomous tacit collusion, that does not rely on explicit communication, is captured by existing competition law. Other unilateral algorithmic harms (such as self-preferencing) are typically considered as sufficiently captured by competition law or the new ex-ante digital regulations. Although some unilateral harms, based on pricing algorithms, may now be more feasible and the existing standard of proof may not yet reflect this new risk (depending on the jurisdiction). Authorities should be aware of these threats given the proliferation of algorithms. There are several potential remedies that competition authorities can adopt to address these algorithmic theories of harm.

Competition authorities are increasingly faced with cases that involve algorithms, and this trend is likely to only increase in the future. Rather than treat these complex algorithms as impenetrable black boxes, many authorities are investing in the knowledge and skills to understand how they work and to identify harm. While still an emerging academic field, there have been considerable advances in methods related to algorithmic auditing and explainable AI. Competition authorities may be able to implement some of these methods when investigating algorithmic harms (although they may be easier to apply to unilateral conduct than coordinated conduct). However, there may also be simpler questions, that require less technical analysis, that an authority can answer to get to assess the core issue of the case.

Endnotes

¹ <https://www.oecd.org/competition/algorithms-and-collusion.htm>

² Algorithmic collusion continues to be a concern for enforcers, such as the US DOJ (<https://www.competitionpolicyinternational.com/dojs-kanter-warns-over-algorithmic-price-fixing-ai/>) and the Dutch ACM (<https://www.acm.nl/en/publications/speech-martijn-snoep-plugging-gaps-antitrust-enforcement> (indirectly, through section on tacit collusion); <https://mlexmarketinsight.com/news/insight/algorithmic-collusion-biggest-concern-for-dutch-competition-enforcer-snoep-says>).

³ The *OECD Handbook on Competition Policy in the Digital Age* (2022) (OECD, 2022^[21]) covers the OECD Competition Division's digital work up to February 2022.

⁴ Some algorithm functionalities may be partially overlapping (e.g., communication virtual assistants can also contain search engines) and many firms use algorithms that combine several of these functionalities.

⁵ <https://itrexgroup.com/blog/what-are-foundation-models/>

⁶ <https://www.microsoft.com/en-us/research/blog/ai-explainer-foundation-models-and-the-next-era-of-ai/>

⁷ <https://www.ft.com/content/c9e97913-bc88-4845-a5b4-fe8f6b813274>

⁸ <https://openai.com/research/gpt-4>

⁹ <https://globalcompetitionreview.com/article/experts-warn-of-antitrust-risks-generative-ai>

¹⁰ <https://www.nytimes.com/2023/05/03/opinion/ai-lina-khan-ftc-technology.html>

¹¹ <https://www.technologyreview.com/2023/03/27/1070285/early-guide-policymaking-generative-ai-gpt4/>

¹² “Recent months have seen AI labs locked in an out-of-control race to develop and deploy ever more powerful digital minds that no one — not even their creators — can understand, predict or reliably control.” Please see: <https://www.ft.com/content/3f584019-7c51-4c9c-b18f-0e0ac0821bf7>

¹³ <https://www.gov.uk/cma-cases/ai-foundation-models-initial-review> and <https://www.bbc.com/news/business-65478156>

¹⁴ “The global AI market is currently worth \$136.6 billion according to GrandViewResearch [...] and is intended to expand at a CAGR (compound annual growth rate) of 38.1% from 2022 to 2030. [...] PwC Global Artificial Intelligence Study shows that AI has a \$15.7 trillion potential contribution to the global

economy by 2030.” <https://saabrds.com/how-much-will-ai-contribute-to-the-global-economy-and-the-industrial-market/>

¹⁵ <https://tech.facebook.com/artificial-intelligence/2021/6/how-ai-makes-online-shopping-easier-for-everyone/>

¹⁶ “Algorithms are used in a wide range of contexts; not only by large digital platforms such as Amazon, Apple, Facebook, Google and Microsoft, but also other firms in a variety of sectors, ranging from transportation (Uber) to freelancing (TaskRabbit/Fiverr), and from stationery suppliers (Staples) to casinos (MGM) and hotel booking sites (Booking.com, Expedia, Hotels.com).” (Google, 2021, p. 13_[114])

¹⁷ The Danish Competition and Consumer Authority (DCCA) found that the number of job postings asking for staff with skills related to price algorithms in Denmark more than tripled between 2007 and 2018 (Danish Competition and Consumer Authority, 2021, p. 4_[6]). The UK Competition and Markets Authority (‘CMA’) found that there was evidence of increasing use of pricing algorithms in offline markets, such as large supermarkets and the retail sale of gasoline (Competition & Markets Authority, 2018, p. 19_[102]). McKinsey found that the adoption of AI by firms has doubled since 2017. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review>

¹⁸ Gartner performed a price optimisation and management software vendor survey in August 2021, reporting the following ranges: “(i) Revenue increases of 1% to 5%; (ii) Margin increases of 2% to 10%; (iii) Elimination of 80% of discount approvals; and (iv) Increase in customer lifetime value of 20%” (Gartner, 2022, p. 17_[34]).

¹⁹ Third-degree price discrimination involves setting different prices for different groups for the same good (e.g., separate prices for different identifiable groups such as children, students, adults and seniors).

²⁰ Please see (OECD, 2017_[4]), (OECD, 2018_[3]) and (OECD, 2020_[18]).

²¹ <https://www.economicsofai.com/nber-conference-toronto-2017>

²² Martijn Snoep, chairman of the ACM, stated at a Blockchain event that algorithmic collusion is currently the biggest concern for the ACM, especially because algorithmic collusion is extremely difficult to detect. During his speech (<https://mlexmarketinsight.com/news/insight/algorithmiccollusion-biggest-concern-for-dutch-competition-enforcer-snoepsays>), he indicated that the ACM is lagging behind developments. However, in order to change this, the ACM has set up a special technology-focused department (Braeken and Versteeg, 2022_[51]).

²³ US case: <https://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace>; UK case: <https://assets.publishing.service.gov.uk/media/57ee7c2740f0b606dc000018/case-50223-final-non-confidential-infringement-decision.pdf>

²⁴ <https://curia.europa.eu/juris/liste.jsf?&num=C-74/14>

²⁵ Press release: https://www.cnmc.es/sites/default/files/editor_contenidos/Notas%20de%20prensa/2021/20211209_NP_Sancionador_Proptech_eng.pdf Case page: <https://www.cnmc.es/expedientes/s000320>

²⁶ https://ec.europa.eu/commission/presscorner/detail/en/IP_18_4601

²⁷ <https://www.propublica.org/article/yieldstar-rent-increase-realpage-warren-sanders>

²⁸ <https://www.reuters.com/article/us-autos-software-pricing-insight-idINKCN1IZ07L>

²⁹ https://www.lalettrea.fr/entreprises_conseil-et-services/2022/11/17/accenture-renault-et-psa-blanchis-dans-l-affaire-du-logiciel-d-optimisation-des-prix,109865672-bre

³⁰ (den Boer, Meylahn and Schinkel, 2022, pp. 1-2_[47]) highlights that there have been several calls to action for policy change to address algorithmic collusion in the academic literature (Harrington, 2018_[108]) (Gal, 2019_[55]) (Beneke and Mackenrodt, 2021_[109]) (Bernhardt and Dewenter, 2020_[110]) (Coglianese and Lai, 2022_[111]) (Gal, 2022_[56]) (Mazundar, 2022_[52]).

³¹ <https://www.gov.uk/government/consultations/algorithms-competition-and-consumer-harm-call-for-information>

³² Fulfillment by Amazon product description “*With Fulfillment by Amazon (FBA), you store your products in Amazon's fulfillment centers, and we pick, pack, ship, and provide customer service for these products*” is here: <https://www.amazon.com/fulfillment-by-amazon/b?ie=UTF8&node=13245485011>

³³ <https://www.oecd.org/competition/remedies-and-commitments-in-abuse-cases.htm>

³⁴ <https://www.oecd.org/daf/competition/interim-measures-in-antitrust-investigations.htm>

³⁵ First-degree price discrimination (also known as perfect price discrimination) involves a firm setting a unique (personalised) price for each unit sold. The firm sets the price at the maximum level for each unit sold (i.e., at the customer’s willingness to pay for that unit) extracting all the consumer surplus. First-degree price discrimination has always been considered difficult to achieve, as it is hard to accurately measure the customer’s willingness to pay. However, with increasingly available and accurate data on customer characteristics, particularly for digital companies, it is becoming more feasible to adopt first-degree price discrimination.

³⁶ Case C-23/14 Post Danmark ECLI:EU:C:2015:651.

³⁷ Case C-413/14 P Intel v Commission ECLI:EU:C:2017:632.

³⁸ The OECD has previously summarised the Bundeskartellamt case against Facebook (OECD, 2020, pp. 51-52_[18]).

³⁹ A short summary of the Kakaku.com case in Japan can be found here: Financial Times, 4 July 2022, “Japanese court ruling poised to make Big Tech open up on algorithms”, <https://www.ft.com/content/f360f766-7865-4821-b740-ca0276efec19>

⁴⁰ The UK CMA launched a consumer law investigation into online hotel booking sites on 27 October 2017: <https://www.gov.uk/cma-cases/online-hotel-booking>

⁴¹ For example, the European Commission can sanction price discrimination as an exploitative abuse using Article 102(c) Treaty on the Functioning of the European Union (TFEU) when a dominant firm applies

“dissimilar conditions” to “equivalent transactions” that lead to some customers being at a “competitive disadvantage” relative to “other trading partners” (Botta and Wiedemann, 2020, p. 390^[36]).

⁴² For example, in Europe, Advocate General Wahl has argued that exploitative forms of price discrimination are “*extremely rare*”, and that they price discrimination should only be sanctioned as an exclusionary conduct, although no court ruling has specified this, thus case law doesn’t clarify the potential treatment of price discrimination as an exploitative abuse (Botta and Wiedemann, 2020, p. 389^[36]).

⁴³ <https://curia.europa.eu/juris/liste.jsf?language=en&num=C-525/16>

⁴⁴ “[...] triggered analogical *Trod Ltd/GB Eye Ltd* case in the UK where *GB Eye Ltd* submitted a leniency application to the UK Competition and Markets Authority acknowledging that it had agreed with *Trod Ltd* its prices in the UK [11]. Both merchants were using the repricing algorithm available on Amazon which is to be adjusted by compete rules determined by each particular merchant [12]. Such rules include, for example, decrease of price for x% for competing goods [13]. The repricer allows to exclude prices of certain merchants from the algorithms by adding such merchants to the ignoring list [14]. Thus, the two merchants had agreed between themselves not to compete on prices and put each other in the ignoring list so that they do not undercut each other prices which resulted in the price-fixing cartel”. Please see: <https://chambers.com/articles/antitrust-implications-of-using-pricing-algorithms>

⁴⁵ In the European Commission’s Digital Markets Act, Article 21 Requests for information and Article 23 Powers to conduct inspections, provide the Commission with the powers to access, obtain and inspect any algorithms and data relevant to implementing the regulation. Please see: <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32022R1925>

⁴⁶ The UK’s Digital Markets, Competition and Consumers Bill introduces information gathering powers in Part 1 “Digital Markets” Chapter 6 “Investigatory powers etc and compliance reports”. Please see: <https://publications.parliament.uk/pa/bills/cbill/58-03/0294/220294.pdf>.

⁴⁷ <https://towardsdatascience.com/think-outside-the-black-box-7e6c95bd2234>

⁴⁸ <https://www.ibm.com/watson/explainable-ai>

⁴⁹ For example, the Japanese Fair Trade Commission (‘JFTC’) considers that it may be feasible and useful to investigate the performance of algorithms for both unilateral conduct and algorithmic concerted practices (Japan Fair Trade Commission, 2021, p. 38^[9]).

⁵⁰ Algorithmic auditing was touched on during the OECD roundtable discussion on *Algorithms and Collusion* in June 2017 which highlighted that “*instead of auditing the algorithm, it would be preferable to audit the data used by the algorithm*” (OECD, 2017, p. 9^[68]).

⁵¹ <https://www.ft.com/content/f360f766-7865-4821-b740-ca0276efec19>

⁵² Cathy O’Neil discussed issues surrounding algorithmic auditing in a recent podcast (1 March, 2023), such as the need for post-deployment testing, industry-wide standards and emerging AI language models. Please see: <https://pareports.com/podcast/24/>.

⁵³ Some technology companies prefer to make their software open source (i.e., the original source code is made freely available and may be redistributed and modified). Please see: <https://gwern.net/complement#open-source-as-a-strategic-weapon>.

⁵⁴ <https://www.theguardian.com/technology/2023/mar/27/twitter-legal-source-code-leaked-elon-musk-github>

⁵⁵ Northeastern University have conducted algorithmic auditing research including “Personalization on Google Search”, “Price Discrimination”, “Surge Pricing on Uber”, “Algorithmic Pricing on Amazon” and “Equitability in Vehicle for Hire Markets”. Please see more details here: <https://personalization.ccs.neu.edu/>

⁵⁶ Local Interpretable Model-agnostic Explanations (‘LIME’) is “*an algorithm that can explain the predictions of any classifier or regressor in a faithful way, by approximating it locally with an interpretable model.*” (Ribeiro, Singh and Guestrin, 2016, p. 1_[81]). For example, a competition authority may want to investigate a machine learning algorithm that provides a company with price recommendations. The machine learning algorithm may rely on input data, with features such as the cost of production and estimates of customer demand, to arrive at a price recommendation. However, it may be a complex non-linear model, that appears to be a “black box”. The authority may want to know how the machine learning algorithm came to provide a specific price recommendation. The authority could use LIME to focus on the specific price recommendation, identifying the input features that were most important in the model reaching that specific decision. A major limitation of the LIME approach is that it can only approximately explain a decision (in the local area around that decision), it cannot globally explain the machine learning algorithm (Dwivedi et al., 2023, pp. 20-21_[85]).

⁵⁷ An anchor is a “*rule that sufficiently “anchors” the prediction locally – such that changes to the rest of the feature values of the instance do not matter*” (Ribeiro, Singh and Guestrin, 2018, p. 1527_[115]). As in the footnote above, an authority may want to understand a machine learning algorithm that provides a company with price recommendations. Anchors are similar to LIME in that they aim to approximately explain the decision locally using a linear estimation. Anchors use if-then rules on the key features that lead to a decision. However, Anchors may apply more broadly than a LIME estimate and thus may better explain the machine learning algorithm’s general decision-making process (Dwivedi et al., 2023, pp. 23-24_[85]).

⁵⁸ Mechanistic Interpretability is “*the study of reverse-engineering neural networks - analogous to how we might try to reverse-engineer a program’s source code from its compiled binary, our goal is to reverse engineer the parameters of a trained neural network, and to try to reverse engineer what algorithms and internal cognition the model is actually doing. Going from knowing that it works, to understanding how it works.*” Please see: <https://www.alignmentforum.org/posts/jLAvJt8wuSFySN975/mechanistic-interpretability-quickstart-guide> and <https://distill.pub/2020/circuits/>.

⁵⁹ The UK’s Digital Markets, Competition and Consumers Bill, Part 1, Chapter 6, Item 67 “Power to require information”, bullet (5) gives the CMA powers to request the firm runs tests: “(a) a requirement for [a person] to vary their usual conduct (whether in relation to some or all users or potential users of any service or digital content that [a person] provides); and (b) a requirement for [a person] to perform a specified demonstration or test”. Please see: <https://publications.parliament.uk/pa/bills/cbill/58-03/0294/220294.pdf>.

⁶⁰ <https://en.agcm.it/en/media/press-releases/2021/12/A528#:~:text=A528%20%2D%20Italian%20Competition%20Authority%3A%20Amazon,for%20abusing%20its%20dominant%20position&text=The%20Authority%20found%20that%20Amazon,review%20by%20a%20monitoring%20trustee.>

⁶¹ https://ec.europa.eu/commission/presscorner/detail/en/IP_17_1784

⁶² <https://globalcompetitionreview.com/survey/rating-enforcement/2020/article/building-platform-digital-enforcement>

⁶³ There are 18 competition authorities that indicated they have a data unit. This increases to 19 if the European Competition Commission is included (given it effectively has staff that perform the role of the data unit in “Unit COMP.DDG1.02 Intelligence, Analysis and Forensic IT Support” and “Unit COMP I.3 Digital Business Solutions”). The complete GCR Rating Enforcement 2022 data can be found here: <https://globalcompetitionreview.com/survey/rating-enforcement/2022>

⁶⁴ <https://www.csc.gov.sg/articles/bring-data-in-the-heart-of-digital-government>

⁶⁵ <https://cmadataconference.co.uk/>

⁶⁶ <https://www.oecd.org/competition/roundtables.htm> and <https://www.internationalcompetitionnetwork.org/>

⁶⁷ Example algorithmic auditing companies include ORCAA (<https://orcaarisk.com/>) and Arthur.AI (<https://www.arthur.ai/>).

⁶⁸ <https://www.oecd.org/competition/workshop-on-competition-in-digital-markets-recent-enforcement-and-new-regulations.htm> and <https://www.internationalcompetitionnetwork.org/working-groups/>

⁶⁹ “The commitments for operational changes are binding only on the French market, but Google said some of them will be made globally.” <https://www.politico.eu/article/france-competition-google-advertising-antitrust-fine/>

⁷⁰ “We [Google] will apply the commitments globally because we believe that they provide a roadmap for how to address both privacy and competition concerns in this evolving sector.” <https://blog.google/around-the-globe/google-europe/path-forward-privacy-sandbox/>

⁷¹ https://www.accc.gov.au/media-release/agencies-form-digital-platform-regulators-forum?utm_source=linkedin_accc&utm_medium=social&utm_campaign=p_edu_g_awa_c_advocacy_regulator_network

⁷² <https://www.concurrences.com/fr/bulletin/news-issues/october-2021/the-dutch-competition-authority-the-data-protection-authority-the-financial>

⁷³ <https://www.gov.uk/government/collections/the-digital-regulation-cooperation-forum>

⁷⁴ https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1094245/Letter_on_Digital_Regulation_Plan.pdf

⁷⁵ https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1071501/DRCF_Annual_Workplan.pdf

⁷⁶ For example: <https://www.fca.org.uk/insight/explaining-why-computer-says-no>

⁷⁷ <https://www.fca.org.uk/publication/multi-firm-reviews/algorithmic-trading-compliance-wholesale-markets.pdf>

⁷⁸ Please see the Updated G20/OECD High-Level Principles on Financial Consumer Protection (updated in 2022) here: <https://www.oecd.org/finance/high-level-principles-on-financial-consumer-protection.htm>

⁷⁹ <https://www.ecchr.eu/en/glossary/hard-law-soft-law/#:~:text=Soft%20law%20instruments%20are%20predominantly,legally%20enforced%20before%20a%20court.>

⁸⁰ <https://oecd.ai/en/network-of-experts>

⁸¹ <https://artificialintelligenceact.eu/> and <https://www.euractiv.com/section/artificial-intelligence/news/meps-seal-the-deal-on-artificial-intelligence-act/>.

⁸² <https://cdei.blog.gov.uk/2021/05/11/the-european-commissions-artificial-intelligence-act-highlights-the-need-for-an-effective-ai-assurance-ecosystem/> and <https://link.springer.com/article/10.1007/s11023-021-09577-4>

Annex A. Prevalence of pricing algorithms

Summary of competition authority surveys and academic research into algorithmic pricing

Jurisdiction and year publication	Time period	Survey scope	Key findings
Europe (2018) (European Commission, 2018, pp. 171,219-220 ^[99])	Between December 2016 and November 2017	Mystery shopping exercise on a (non-random) sample of 160 websites across 4 product categories (airline tickets, hotels, sports shoes, and TVs) and 8 EU Member States (Czech Republic, France, Germany, Poland, Romania, Spain, Sweden, United Kingdom)	<ul style="list-style-type: none"> • The European Commission (EC) found: <ul style="list-style-type: none"> ○ 61% of the websites personalised ranking of offers. ○ 6% of tests recorded personalised pricing (indicated by price differences) and the median price difference was less than 1.6%. <ul style="list-style-type: none"> – 22% of websites (34 of 153) exhibited some tests with price differences that couldn't be explained by random variation, although this was often close to zero. – 10% of websites (16 of 153) had average price differences above 1%, with the largest average difference just under 4%. All these websites belonged to the airline tickets or hotels sectors.
Europe (2017) (European Commission, 2017, pp. 17,22,24,29-32,175 ^[100])	Between June 2015 and March 2016.	Survey of retailers across EU Member States, with a variety of sizes and selling a range of product categories, nearly all of which at least operated online, ultimately receiving responses from 1051 retailers.	<ul style="list-style-type: none"> • The European Commission (EC) found: <ul style="list-style-type: none"> ○ 49.0% of these retailers tracked competitor prices (515 of 1051 retailers), of which 66.6% used price monitoring software (monitoring algorithm) (343 of 515 retailers), with larger companies more likely to track competitor prices than smaller companies. ○ Of those using price monitoring software: 78% changed their prices in response to competitor price changes (78% of 343 retailers, so around 268 retailers, which is around 25% of all retailers), and 35% used specialised software (pricing algorithm) (35% of 343 retailers, so around 120 retailers, which is around 11% of all retailers) (a combination of 8% that solely use specialised pricing software and 27% that use both manual and automatic price adjustments).
Norway (2021) (Norwegian Competition Authority, 2021, pp. 2-7 ^[101])	In Spring and Autumn of 2020.	Survey of 51 firms from various sectors of the Norwegian economy.	<ul style="list-style-type: none"> • The Norwegian Competition Authority (NCA) found: <ul style="list-style-type: none"> ○ 55% of respondent firms used monitoring algorithms (25% used their own software, 14% used an external data source (such as a price comparison website), and 16% used a combination of both). ○ 20% of respondent firms used pricing algorithms (with the survey also indicating that the use of artificial intelligence was not widespread).
Denmark (2021) (Danish Competition and Consumer Authority, 2021, p. 4 ^[6])	Early 2019.	Survey of 106 e-commerce companies.	<ul style="list-style-type: none"> • The Danish Competition and Consumer Authority (DCCA) found: <ul style="list-style-type: none"> ○ 17% respondent firms use pricing algorithms. ○ Of respondent firms that use pricing algorithms: <ul style="list-style-type: none"> – Just under 30% had algorithms that provided information that was used in pricing, just under 60% used algorithms that provided a price recommendation (but ultimately the price was set manually), and around 35% used algorithms that directly control pricing.

			<ul style="list-style-type: none"> –65% primarily relied on data about their own company, 47% used information on competitor prices, and only 12% used information on the firm’s customers. –80% used pricing algorithms for online sales, however around 33% also used pricing algorithms to set prices in stores. –80% developed the pricing algorithm internally at the company, while 20% developed the pricing algorithm in collaboration with a third-party.
The Netherlands (2019) (Authority for Consumers and Markets, 2019, pp. 5,22-23,47 ^[101])	Between 17 October and 12 December 2019.	Survey of 2,125 firms operating across a range of sectors in the Dutch economy.	<ul style="list-style-type: none"> • The Netherlands Authority for Consumers and Markets (ACM) found: <ul style="list-style-type: none"> ○ 36% of firms use the prices of competitors to set their own prices, with no differences between smaller and larger firms. ○ Of which: 16% (so 6% of all firms) used pricing algorithms (defined as a formula that automatically calculates the price of a product or service based on data), with no significant differences between smaller and larger firms.
Portugal (2019) (Autoridade da Concorrência, 2019, pp. 43-45 ^[13])	April 2019.	Survey of 38 firms, targeting those with an active online presence in Portugal in several economic sectors.	<ul style="list-style-type: none"> • The Portuguese Autoridade da Concorrência (AdC) found: <ul style="list-style-type: none"> ○ 47.4% of inquired firms systematically tracked online prices of competitors, of which 77.8% used price monitoring software (monitoring algorithm) (37% of all inquired firms). ○ Of those using price monitoring software: 78.6% adjust their prices in response to competitor price changes, with all of them doing it manually, but one firm stating it also does them automatically. ○ The use of pricing algorithms is uncommon, with only 7.9% of inquired firms using software to automatically set prices.
UK (2018) (Competition & Markets Authority, 2018, pp. 37-42 ^[102])	-	Call for contributions and mystery shopping.	<ul style="list-style-type: none"> • The UK competition authority found no evidence of personalised pricing: <ul style="list-style-type: none"> ○ In 2012, the UK Office of Fair Trading (OFT) launched a call for contributions and found no evidence of personalised pricing. ○ In 2017, the CMA conducted research on websites using several user profiles and found no evidence of personalised pricing.
Singapore (2021) (Lee, 2021, pp. 3-6 ^[103])	Between August 2020 and April 2021	Survey of 111 firms, across a range of sectors in the Singaporean economy (although only 64 firms participated in e-commerce and thus indicated whether or not they used algorithmic pricing).	<ul style="list-style-type: none"> • This was a survey performed by an academic researcher. They found that of the 64 firms that participated in e-commerce: <ul style="list-style-type: none"> ○ 8 (12.5%) firms adopted algorithmic pricing. ○ 56 (87.5%) firms did not adopt algorithmic pricing.
US (2016) (Chen, Mislove and Wilson, 2016, pp. 1,4,7 ^[104])	Over four months of price data (three months from 15 September to 8 December 2014 and one month from 11 August to 21 Sept. 2015).	Academic researchers web-scraped all merchants selling any of 1,641 best-seller products on amazon.com (approximately 30,000 sellers (Competition & Markets Authority, 2018, p. 18 ^[102]))	<ul style="list-style-type: none"> • This was a survey performed by academic researchers. The authors developed a methodology to identify algorithmic pricing and uncovered at least 500 sellers that they considered very likely to be using algorithmic pricing, which represents 2.4% of all sellers in the dataset.

Source: Provided in the column “Jurisdiction and year publication”.

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