Organisation for Economic Co-operation and Development

DAF/COMP/GF/WD(2025)4

Unclassified

English - Or. English

18 November 2025

DIRECTORATE FOR FINANCIAL AND ENTERPRISE AFFAIRS
COMPETITION COMMITTEE

Global Forum on Competition

Artificial Intelligence and Competitive Dynamics in Downstream Markets

- Session I -

1 December 2025

This contribution is submitted by CUTS under Session I of the Global Forum on Competition to be held to be held on 1-2 December 2025.

More documentation related to this discussion can be found at: oe.cd/aidm.

Mr Antonio Capobianco [Antonio.Capobianco@oecd.org].

JT03576993

Table of contents

FIGURES

TABLES

CUTS

AI and Downstream Market Competition: Addressing Abuse, Ensuring Access, and Promoting Innovation[1]

1. Introduction

1. AI is no longer a futuristic concept, it is a foundational technology driving innovation, efficiency, and transformation across industries. From predictive analytics in logistics to generative models in content creation, AI is embedded in both upstream and downstream layers of digital supply chains. However, the concentration of AI resources particularly proprietary datasets, computing infrastructure, and foundational models raises significant competition concerns.

2. Downstream markets, where AI applications interface directly with consumers and businesses, are particularly vulnerable to exclusionary practices. Dominant firms may leverage control over upstream AI inputs to foreclose rivals, manipulate consumer behaviour, or entrench market power. This paper investigates these dynamics, evaluates legal frameworks, and proposes policy interventions to ensure that AI serves as a catalyst for inclusive growth rather than a tool for market control.

2. Defining Downstream Markets in the AI Supply Chain

3. In competition law, defining a market is essential for assessing the scope of competitive conduct and its effects. Markets are typically delineated by product and geographic boundaries, but in digital ecosystems, it is equally important to locate a firm's position within the supply chain. This distinction between upstream and downstream markets helps regulators understand how conduct at one level can shape outcomes at another.

4. According to the European Commission's Antitrust and Control of Concentrations (2002)[2], an upstream market is "the market at the previous stage of the production/distribution chain," while a downstream market is "the market at the next stage." These definitions are particularly relevant in digital markets, where supply chains are often non-linear and interdependent.

5. In traditional supply chains, the structure typically follows:

- Producer
- Wholesaler
- Retailer

[1] Authors: Dr. Drishti Parnami, Bhavika Khatter, and Gazal Arora from CUTS Institute for Regulation & Competition (CIRC); Vidhi Maharishi, CUTS International. The authors acknowledge the guidance and support of Sohom Banerjee and Ujjwal Kumar, CUTS International.

[2] *Concurrences*, https://www.concurrences.com/en/dictionary/downstream-market-117440 (Oct. 20, 2025).

- Consumer

6. The supply chain might also differ for different markets. Identifying whether a firm operates at the upstream or downstream level is vital, since it determines how its conduct may influence competitive dynamics along the supply chain. Ustream and downstream describe the relative position of different players or their product in the supply chain. The most 'upstream' provider is the one providing the most basic product (usually the raw material of a product) and next in line of the supply chain are subsequent 'downstream' players, who are the buyers of upstream products. The significance of a buyer in the downstream market is a key factor in determining whether a competition concern may arise; if the buyer lacks market power downstream, the likelihood of appreciable harm to consumers is minimal.[3]

7. Courts and competition authorities have consistently distinguished upstream/downstream markets to assess adverse effects in merger effects, vertical foreclosure, abuse of dominance and refusal to supply in a variety of industries. The United States Court of Appeals for the Ninth Circuit in *Alaska Airlines v. United Airlines*[4] opined that a monopolist has the power to eliminate competition in the downstream market if the facility is essential in nature. This view was further reinforced in *Aerotec Int'l v. Honeywell*[5].

3. AI Supply chain architecture

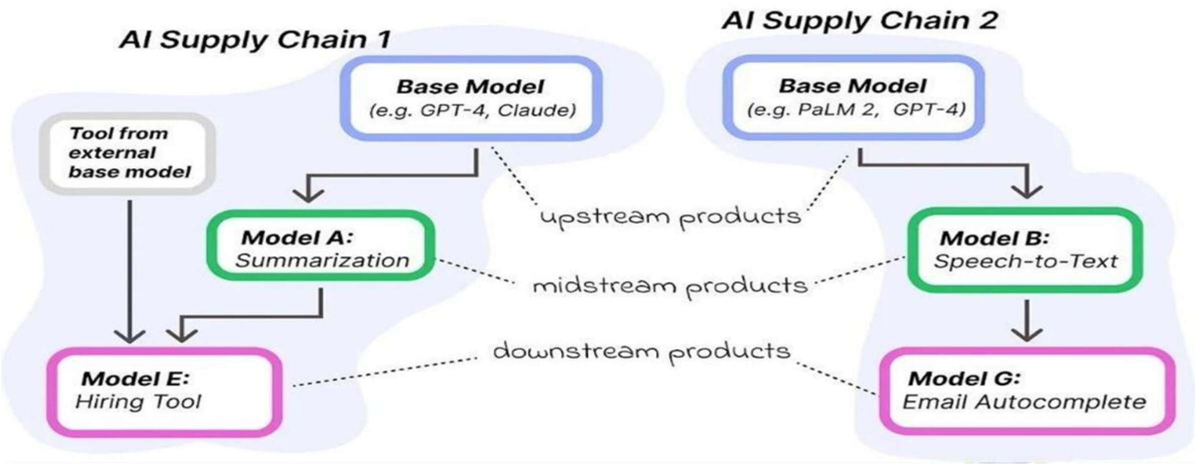
8. In AI induced supply chains, base models constitute "upstream" AI which are then used by companies for their specific domain application, which is considered as "midstream" and "downstream" layers of the AI supply chain. Downstream AI supply chain directly interfaces with end users such as AI-driven shopping apps, hiring tools or a writing assistant app etc. The availability of base model in the upstream market makes AI in the downstream market more accessible as, base AI model provides a raw material which would have been expensive and cumbersome to curate from scratch. Figure 1 demonstrates an AI supply chain.

[3] Commission Notice — Guidelines on Vertical Restraints, para. 194, *COMMISSION NOTICE,* EUROPEAN COMMISSION, Brussels, SEC (2010) 411, SEC (2010) 413, 2010 O.J. (C 130) 1 (EU).

[4] Alaska Airlines, Inc. v. United Airlines, Inc., 948 F.2d 536 (9th Cir. 1991).

[5] Aerotec Int'l, Inc. v. Honeywell Int'l, Inc., 836 F.3d 1171 (9th Cir. 2016).

Figure 1.



Source: (Source[6])

9. The AI supply chain consists of multiple interlinked layers, each with distinct competitive implications:

3.1. Upstream AI

10. This layer includes:

- Foundational models (e.g., large language models, vision models)
- Proprietary datasets
- Specialized computing infrastructure (e.g., GPUs, TPUs)

11. Upstream AI providers supply the raw materials such as data and algorithms that power downstream applications. These inputs are often expensive to develop and difficult to replicate, creating high entry barriers.

3.2. Midstream AI

12. Midstream actors fine-tune base models for specific domains, such as healthcare, finance, or logistics. This layer involves:

- Domain adaptation
- Model refinement
- API development

13. Midstream firms may rely on upstream providers for access to foundational models and data, making them vulnerable to exclusionary practices.

[6] Sarah H. Cen, Aspen Hopkins, Andrew Ilyas, Aleksander Madry, Isabella Struckman & Luis Videgaray, *On AI Deployment: AI Supply Chains (and Why They Matter)*, Thoughts on AI Policy (Jun. 18, 2023), https://aipolicy.substack.com/p/supply-chains-2.

3.3. Downstream AI

14. Downstream applications interface directly with end users. Examples include:

- AI-driven shopping platforms
- Hiring and recruitment tools
- Writing assistants
- Predictive maintenance software

15. These applications depend on upstream and midstream inputs. If access to foundational models or data is restricted, downstream innovation may be stifled.

16. Identifying upstream and downstream market also particularly becomes relevant when the dominant upstream market player withholds access to an "essential facility" or uses AI in the downstream market to collude, which affects effective competition in the downstream market. In the *Italian Rail Infrastructure case*[7], the upstream market was the provision of railway infrastructure (tracks, stations etc.), while the downstream market consisted of rail transport services provided to passengers and freight customers. By refusing access to the rail network, the infrastructure manager effectively foreclosed rivals from operating in the downstream transport services market. Since competing rail operators could not viably duplicate the infrastructure, denial of access amounted to eliminating effective competition in the downstream market. Similarly, in the Android Auto case[8], Google launched 'Android Auto' app which enabled users to use apps available on Android directly on the screen of the information system of motor vehicles. Google offered templates of apps that were interoperable with Android Auto. However, Google refused to provide this access to the Juice Pass app (an app which enables users to search and book charging stations for electric vehicles on map), the court held that access to Android Auto was essential to providers of Juice pass apps to access the market. Google's refusal eliminated effective competition in the market and hence, Google was held liable under Article 102 TFEU.

3.4. Interdependence and Competitive Risks

17. The layered structure of the AI supply chain creates interdependencies. Dominant upstream firms can:

- Withhold access to essential inputs
- Impose discriminatory terms
- Engage in self-preferencing through vertical integration

18. Such conduct can distort competition in downstream markets, reduce consumer choice, and entrench market power.

19. AI can also be used in the downstream market to induce collusion such as in the recent allegation pertaining to RealPage, where it has been alleged that the property

[7] Georg Verkehrsorganisation GmbH v. Ferrovie dello Stato SpA, COMP/37.685 GVG/FS

[8] Alphabet and Others vs. Autorità Garante della Concorrenza e del Mercato, Case C-233/23.

management software company has artificially inflated the rental prices using algorithmic pricing model[9].

4. Pro and anti-competitive effects of AI

4.1. Pro-Competitive Effects of AI Use

20. AI adoption fosters dynamic efficiencies and strengthens innovation incentives across both upstream and downstream markets. Firms today compete not merely on price but increasingly on their capacity for technological adoption and integration, thereby driving innovation-led competition. This process generates substantial learning effects, as firms deploying AI accumulate richer datasets and operational expertise over time. Such cumulative learning can reduce production and distribution costs, enhance process efficiencies, and ultimately improve consumer welfare. Additionally, AI enables seamless coordination between offline and online distribution channels, mitigating risks of intra-brand channel conflict for instance, preventing situations where a manufacturer's online store undercuts its authorized retailers.

21. From a regulatory standpoint, AI-driven systems enhance transparency and compliance in vertical agreements. Automated monitoring tools can detect deviations in resale price maintenance or other restrictive vertical practices more efficiently, thereby strengthening adherence to competition norms. In markets characterized by active rivalry, such transparency reduces enforcement costs for regulators and deters opportunistic conduct by firms, reinforcing a culture of compliance.

22. At the same time, AI empowers consumers by improving market matching efficiency. Through advanced recommendation algorithms, consumers can navigate overwhelming product choices more effectively, accessing goods and services that best align with their preferences. This personalized matching reduces search costs[10], mitigates information asymmetry, and enhances consumer surplus. Collectively, these effects promote both allocative and dynamic efficiency, deepening overall market performance.

23. In essence, AI serves as a catalyst for competition by simultaneously fostering innovation, improving compliance mechanisms, and empowering consumers. However, the realization of these benefits hinges on preserving market contestability and preventing dominant firms from converting AI-enabled advantages into exclusionary barriers. Effective governance of AI deployment thus becomes critical to maintaining a dynamic equilibrium between innovation incentives and fair competitive conduct.

[9] U.S. Department of Justice. (2024, December 6). *Justice Department sues RealPage for algorithmic pricing scheme that harms millions of American renters.* U.S. Department of Justice Archives. https://www.justice.gov/archives/opa/pr/justice-department-sues-realpage-algorithmic-pricing-scheme-harms-millions-american-renters

[10] Goldfarb, A. & Tucker, C. (2019). *Digital Economics.* Journal of Economic Literature, 57(1), 3–43.

4.2. Anti-Competitive Effects of AI Use

24. While AI holds significant potential to enhance competition, its deployment also introduces a range of **anti-competitive risks** that merit careful scrutiny. ***Firstly***, the rise of **algorithmic collusion and tacit coordination** challenges traditional antitrust frameworks. Even in the absence of explicit agreements, self-learning AI tools may recognize mutual interdependence among competitors and align prices to avoid destructive competition. Such **tacit collusion**, emerging from algorithmic interaction rather than human intent, remains notoriously difficult to detect and address under existing competition law doctrines.

25. ***Secondly***, concerns arise around **self-preferencing and vertical integration** within AI-driven platforms. Large intermediaries such as Amazon or Alibaba may leverage algorithms to subtly privilege their own downstream businesses through biased product rankings, search visibility, or preferential pricing. This practice undermines the principle of **neutral intermediation**, distorting market access for independent retailers and eroding consumer choice.

26. ***Thirdly***, AI-driven personalization can exacerbate **information asymmetries** and lead to **consumer exploitation**. Personalized recommendations, while convenient, may not always enhance welfare; instead, they can strategically nudge users toward higher-margin or sponsored products, reinforcing behavioural lock-in. Such manipulation often through **dark patterns**, blurs the line between consumer assistance and exploitation.

27. ***Fourthly***, **algorithmic exclusion and discrimination** pose another emerging concern. AI systems, whether in delivery logistics or seller credit scoring, may encode biases that systematically exclude specific retailers or consumer groups. This results in forms of **digital redlining**, where algorithmic decisions entrench inequality and limit equitable market access.[11]

28. ***Fifthly***, increasing reliance on a **single AI provider** for critical industry functions such as pricing optimization or logistics management raises **standardization and dependency risks**. When a dominant upstream firm supplies these systems across competitors, the market risks sliding into **hub-and-spoke collusion**, diminishing technological diversity and innovation incentives.[12]

29. ***Lastly***, **privacy harms** are increasingly viewed as a competition concern. Extensive data collection underpins AI-driven personalization, leaving consumers with a **privacy-for-quality trade-off**. In markets lacking viable alternatives, consumers may be coerced into accepting invasive data practices, turning privacy loss into a manifestation of **market power abuse**.[13]

30. Taken together, these risks underscore the need for competition authorities to evolve their analytical tools shifting from traditional price-centric assessments toward a more holistic view that accounts for algorithmic behaviour, data power, and the structural implications of AI-driven markets.

[11] Narayanan, A., Hu, Y., & Shmatikov, V. (2008). *De-anonymizing Social Networks.* IEEE Symposium on Security and Privacy.

[12] Petit, N. (2019). *Big Tech and the Digital Economy: The oligopoly Scenario.* Oxford University Press.

[13] Stucke, M. & Grunes, A. (2016). *Big Data and Competition Policy.* Oxford University Press.

5. Digital Market: definition and test

5.1. Understanding Digital and Platform Markets Dynamics

31. AI acts as a transformative force in downstream markets by analysing large datasets to automate decisions, predict consumer preferences, and optimise operations. This leads to greater efficiency, lower costs, and improved quality of products and services. Firms that integrate AI effectively gain advantages in pricing, customisation, and speed of innovation, which can increase market concentration. AI also amplifies the value of data and network effects, as insights from one market or product can enhance performance in other areas, creating a reinforcing cycle of competitiveness.

32. While the EU DMA does not define "digital markets" per se but it does define "digital sector" as "*the sector of products and services provided by means of, or through, information society services*." They often operate across regions and countries, though local regulations, language, culture, and consumer behaviour can influence their functioning. Platform markets are a specific type of digital market in which online platforms act as intermediaries, connecting different user groups. In report on "Competition Policy for the Digital Era," commissioned by Competition Commissioner Vestager, the authors Crémer, de Montjoye and Schweitzer[14] do not call the instrument of market definition as such into question, but state that:

"In the case of platforms, the interdependence of the markets becomes a crucial part of the analysis whereas the role of market definition traditionally has been to isolate problems. Therefore . . . less emphasis should be put on the market definition part of the analysis, and more importance attributed to the theories of harm and identification of anti-competitive strategies."[15]

33. These markets are characterised by strong network effects, where the platform's value rises as more users participate. While many platform markets operate globally, local factors such as payment systems or regulations may shape their characteristics.

34. Several structural factors define digital and platform markets. Network effects encourage rapid growth and concentration. Economies of scale arise from high upfront development costs but low marginal costs for reproduction and distribution. Economies of scope emerge when firms leverage existing infrastructure or data to expand into related products. Data itself is a critical economic asset, driving innovation, efficiency, personalisation, and decision-making. In platform markets, multi-sided interactions and cross-subsidisation add further complexity. AI-enabled advantages may spread globally, but their impact varies according to local data availability, infrastructure, and adoption patterns.

5.2. Economic Tests to Assess Market Power in Digital Markets

35. AI shapes competition even in markets where the product or service is not itself AI-based. In digital markets, market power must be assessed by considering factors beyond price, including innovation, quality, and control over data. Traditional tools such as the SSNIP (Small but Significant Non-transitory Increase in Price) test are of limited use in these markets, especially when firms provide free or low-cost services, as price alone does

[14] Crémer, de Montjoye and Schweitzer, Competition policy for the digital era (2019), p. 46.

[15] Jens-Uwe Franck & Martin Peitz, Market Definition in the Platform Economy, CRC TR 224 Discussion Paper Series 2021, final version Cambridge Yearbook of European Legal Studies (CYELS) 23 (2021), https://doi.org/10.2139/ssrn.3773774.

not capture competitive landscape. The SSNIP test examines whether a price increase would lead customers to switch or producers to redirect output, identifying competitive constraints. However, when products or services are offered for free, data has no visible or permanent price, making SSNIP inapplicable[16].

36. In such cases, surveys of customer behaviour can be used, but they must account for biases, especially hypothetical bias. Zero pricing does not make substitution evaluation impossible. Instead, market definition must consider multi-sided platforms and indirect network effects, recognising that competition may occur on non-price factors such as quality, innovation, privacy, and sustainability.

37. The SSNDQ (Small but Significant Non-transitory Decrease in Quality) test adapts SSNIP for zero-price or quality-driven markets. It examines whether a firm could reduce the quality of its AI-enhanced service, such as predictive analytics, personalised recommendations, or process automation, without losing customers. The SSNDQ test allows the assessment of competition in contexts where non-price factors are the primary drivers. For two-sided platforms, it can define the user side of the market where services are free, as a reduction in quality could prompt users to switch platforms[17]. The utility of the SSNDQ lies in its ability to inculcate a quantitative evaluation of quality factors in the market definition process.[18] Experts have observed that the SSNDQ test is necessary for defining markets and assessing market power in sectors subject to rapid technological change.

38. In 2019, CUTS International did a primary study on relevant market in the ride-sharing industry in the Delhi-NCR region, applying SSNIP and SSNDQ framework. The findings suggested that both the test are not substitutes of each other.[19] Hence, it is not appropriate for the regulators to use SSNIP as a substitute test in digital platforms as both the test focus on different assessment criteria which result in different relevant market.This distinction is particularly important for regulators in digital and AI-driven markets, which are highly dynamic and rapidly evolving. AI strengthens market power in downstream markets by improving efficiency, lowering costs, offering superior quality or personalised services, and accumulating proprietary data that competitors cannot easily replicate. Assessing market power in such contexts requires combining SSNIP or SSNDQ tests with analysis of network effects, switching costs, control over data, and multi-sided market dynamics.

[16] David S Evans and Richard Schmalensee, '*The Antitrust Analysis of Multi-Sided Platform Businesses*' in ROGER BLAIR AND DANIEL SOKOL (EDS), OXFORD HANDBOOK ON INTERNATIONAL ANTITRUST ECONOMICS (Oxford University Press 2014).

[17] OECD, THE ROLE AND MEASUREMENT OF QUALITY IN COMPETITION ANALYSIS, DAF/COMP(2013)17, (Oct 28, 2013), *available at,* https://www.oecd.org/competition/Quality-in-competition-analysis-2013.pdf.

[18] OECD, The Role and Measurement of Quality in Competition Analysis, (2013) available at http://www.oecd.org/competition/Quality-in-competition-analysis-2013.pdf.

[19] An Evidence-Based Analysis of Relevant Market in Delhi-NCR Region, 2019, CUTS International; evidence-based-analysis-the-case-of-ride-sharing-in-delhi-national-capital-region.pdf.

5.3. Market Power and Entry Barriers in Digital and AI Markets

39. Market power exists on a spectrum from perfect competition, where no firm holds power, to monopoly, where a single firm dominates. The threshold for dominance is defined in economic terms as "significant market power," implying that a firm can act independently of competitors, customers, and consumers, often reflected in its ability to raise prices profitably without losing business.

40. In multisided digital platforms, actual competition may exist, but potential competition plays a critical role. Firms holding and exploiting large datasets can create barriers to entry, strengthen network effects, and increase switching costs, reinforcing market power. Market shares, while still indicative of strength, provide only a partial view of a platform's ability to act independently. Analysing barriers to entry and expansion is therefore essential.

5.4. Data as a Source of Market Power

41. The possession of data can be a source of market power, but its true value lies in its use. Market shares may be better assessed by the turnover generated in a potential market for a specific type of data, reflecting the firm's ability to extract value rather than the intrinsic worth of the dataset itself. Continuous data collection and access, coupled with algorithms to extract insights, are necessary, as data quickly becomes outdated. Data externalities also reinforce power: established firms benefit from large user-generated datasets, which improve AI offerings and create positive feedback loops that disadvantage new entrants[20].

42. Access to data can create bottlenecks, particularly when it is unavailable to potential competitors or used in adjacent markets. Even the 2019 Competition Law Review Committee (CLRC) report, recognises 'data' and 'revealed preferences' as non-monetary considerations in assessment of market power.[21] This highlights the importance of potential competition in market power analysis and explains why policymakers emphasise regulation and data accessibility to prevent excessive concentration and ensure benefits are widely shared.

6. AI related Anti-Competitive Risks in Downstream Markets

43. The structure of AI markets in downstream applications is shaped by significant economies of scale and scope. Advanced AI requires substantial investment in computation, data acquisition, and specialised talent, which creates natural concentration and entry barriers. Dominant firms can reinforce their position through lock-in effects and bundling, further limiting competition and innovation in markets where AI is an input rather than the primary product.

44. As AI becomes increasingly embedded in commercial applications, its deployment in downstream markets raises a host of competition concerns. These risks are not merely

[20] Christophe Samuel Hutchinson, '*Potential abuses of dominance by big tech through their use of Big Data and AI*', JOURNAL OF ANTITRUST ENFORCEMENT, (2022), 1–26

[21] Competition Law Review Committee, Report of the Competition Law Review Committee (July 2019), https://www.ies.gov.in/pdfs/Report-Competition-CLRC.pdf.

theoretical; they are already manifesting in real-world cases across jurisdictions. Below are the primary anti-competitive risks associated with AI in downstream markets:

6.1. Refusal to Deal and Essential Facilities

45. The essential facilities doctrine originally developed in infrastructure sectors faces new relevance in digital markets. With the rise of digital markets, a central question emerges: can big data and AI be classified as “essential facilities,” thereby imposing obligations on dominant players to provide access to competitors? While earlier applications of the essential facilities doctrine were limited to traditional infrastructure sectors, the digital economy challenges regulators to adapt these principles to data-driven markets. As big data and AI increasingly shape competitive advantage, regulators worldwide are debating whether dominant platforms should be compelled to share data with rivals.

6.1.1. The Essential Facilities Doctrine: Traditional Application

46. Under the European framework, refusal to deal constitutes abuse of dominance when a dominant firm denies access to an indispensable input. The landmark Oscar Bronner case[22] established three conditions: (i) refusal likely eliminates all competition, (ii) refusal lacks objective justification, and (iii) the input is indispensable, meaning no actual or potential substitute exists.

47. The Microsoft decision[23] exemplifies strict application: Microsoft, with 95% market share, was found to have breached Article 82 EC by refusing to supply interoperability information to rivals, thereby foreclosing competition. Similarly, in Slovak Telekom, the CJEU clarified that the Bronner test applies only to outright refusals. Implicit refusals such as imposing unfair conditions or delays may constitute abuse even without proof of indispensability.

48. The principle emerging from these cases is that an input must be genuinely indispensable, not merely “good to have.” The indispensability test is central in distinguishing competitive harm from legitimate business choices.

6.1.2. Data and AI as Potential Essential Facilities

49. Big data and AI are the backbone of digital markets. They enable targeted advertising, personalized pricing, product improvement, and innovation strategies. Platforms like Google, Amazon, and Facebook leverage data-driven feedback loops: consumer data improves services, which attracts more users, generating more data, reinforcing dominance.

50. Scholars are divided on whether data qualifies as indispensable. One school argues that data is not monopolizable, multi-homing[24], abundance, and open-source tools reduce barriers to entry. Examples like Slack and Snapchat show that innovation can disrupt incumbents without massive data reservoirs. Conversely, others highlight that scale, scope,

[22] *Oscar Bronner GmbH & Co. KG v. Mediaprint Zeitungs- und Zeitschriftenverlag GmbH & Co. KG*, Case C-7/97, [1998] E.C.R. I-7791.

[23] *Microsoft Corp. v. Commission of the European Communities*, Case T-201/04, [2007] E.C.R. II-03601.

[24] Sokol, Daniel D. And Comerford, Roisin, 2016. ‘’Antitrust and Regulating Big Data’’. In George Washington Law Review, Vol. 23, 2016. p. 1137.

and speed of data processing confer unique advantages, making replication nearly impossible for new entrants.

51. The Cegedim case[25] before the French Autorité illustrates this complexity. Although Cegedim's "OneKey" database was highly valuable, it was not deemed indispensable, since alternatives existed. Yet, discriminatory refusal to supply was still penalized. The case suggests that even if data does not qualify as an essential facility, conduct involving discriminatory access can amount to abuse.

52. In digital markets, the essential facilities doctrine is gaining renewed relevance. For example:

- **EU Microsoft Case**:[26] Microsoft was found to have abused its dominant position by refusing to supply interoperability information for its server operating systems. This refusal eliminated effective competition in the downstream market for workgroup server systems.
- **Android Auto Case**:[27] Google denied access to its Android Auto platform to Juice Pass, an app for electric vehicle charging stations. The court held that access was essential for market entry, and Google's refusal constituted abuse of dominance.

53. These cases demonstrate that AI inputs especially data and platform access can function as essential facilities. When access is denied, downstream innovation and competition are jeopardized.

6.1.3. Indian Perspective on Refusal to Deal

54. The Competition Act, 2002 does not explicitly use the term "essential facility," but Section 4 prohibits abuse of dominance, including denial of market access. Indian jurisprudence has applied essential facilities reasoning in traditional infrastructure cases.

55. The digital sector has recently come under scrutiny. In Matrimony.com v. Google[28], the CCI imposed penalties for search bias and unfair terms, emphasizing that dominant digital players have "special responsibility" due to network effects and their role as gateways to the internet. The CCI's 2020 e-commerce market study[29] further highlighted risks of platform neutrality, exclusive contracts, and deep discounting. Importantly, the Google case marked the CCI's first acknowledgment that big data could raise competition concerns.

56. Although CCI has not yet classified big data as an essential facility, its recognition that data-driven models may compromise consumer autonomy suggests future enforcement could move in this direction.

[25] *Autorité de la concurrence*, Dec. No. 14-D-06 (July 8, 2014).

[26] *Microsoft Corp. v. Commission of the European Communities*, Case T-201/04, [2007] E.C.R. II-03601.

[27] Id at 7.

[28] CCI Case No. 7 and 30 of 2012.

[29] Competition Commission of India, *Market Study on E-Commerce in India: Key Findings and Observations* (2022),https://www.cci.gov.in/images/marketstudie/en/market-study-on-e-commerce-in-india-key-findings-and-observations1653547672.pdf

6.1.4. Challenges in Treating Data/AI as Essential Facilities

- Indispensability Test: Unlike railways or telecom local loops, data is non-rivalrous, abundant, and often substitutable. Establishing indispensability is harder in digital markets.
- Innovation Incentives: Forcing firms to share data may undermine incentives to invest in data collection, AI training, and technological advancement.
- Dynamic Markets: Digital markets evolve rapidly; regulation must be proportionate and avoid stifling innovation.
- Multi-Homing and Substitutability: Consumers often share data across multiple platforms, weakening exclusivity arguments.
- Risk of Overreach: Premature classification of data as an essential facility may lead to regressive regulation, slowing digital growth in developing economies.

Table 1. Global Approaches to Data as an "Essential Facility"

Jurisdiction	Legal Basis	Recent Developments	Approach to Data/AI
EU	Art. 102 TFEU + Digital Markets Act (2023)	Microsoft (2004), Slovak Telekom (2020), Google AdTech case (2023)	Proactive obligations on "gatekeepers" – data-sharing, interoperability, ban on self-preferencing
US	Sherman Act, Clayton Act	DOJ vs. Google (search), FTC vs. Meta (data acquisitions), FTC vs. Amazon (self-preferencing)	Litigation-based, case-by-case – no blanket data-sharing, but focus on exclusionary conduct
India	Competition Act, 2002 + Draft Digital Competition Law (DCLC, 2024)	Matrimony.com v. Google (2018), E-commerce Market Study (2020)	Moving toward hybrid regime: SSDE framework to impose ex-ante obligations on dominant digital firms
UK	Digital Markets, Competition and Consumers Act (2024)	CMA powers to designate "Strategic Market Status" firms	Tailored codes of conduct; can require interoperability and fair access in specific markets
China	Anti-Monopoly Law (AML, amended 2022) + Platform Economy Guidelines (2021)	Alibaba "er xuan yi" case (2021), SAMR scrutiny of Tencent, Meituan, and AI platforms	Strong ex-ante oversight: bans on data-related exclusion (e.g., "choose one of two"), merger scrutiny in digital/AI, emphasis on state-driven data governance and fair platform access

57. The essential facilities doctrine was developed in the context of traditional infrastructure but finds renewed relevance in digital markets. While big data and AI undeniably underpin modern competition, their classification as essential facilities remains contentious. The European and Indian experiences reveal that indispensability is the linchpin of the doctrine, and overextension risks stifling innovation.

58. In India, the CCI has begun to recognise the competitive risks posed by data-driven and AI-enabled platforms. However, granting data the status of an *essential facility* at this stage could be premature and counterproductive. A more measured approach that is focused on preventing discriminatory conduct, ensuring interoperability, and addressing structural risks through merger control would offer a sounder regulatory path. Although big data may not yet qualify as an essential facility in the strict legal sense, its growing importance in digital markets warrants close and continuous oversight.

6.2. Self-Preferencing

59. Self-preferencing (SP) refers to a situation in which a digital platform gives preferential treatment to its own products or services over those of rivals operating on the same platform. While such conduct may seem like a natural extension of a firm's right to promote its own offerings, it raises significant competition law concerns when carried out by a dominant platform. In traditional markets, firms naturally prefer their own products supermarkets promote private labels, and manufacturers highlight their brands. However, in digital platform markets, the issue becomes complex because dominant platforms act both as *market facilitators* and *market participants*. When a platform that controls market access privileges its own products, it can significantly alter competitive dynamics.

60. As digital markets are characterized by strong network effects, multi-sidedness, and reliance on data and algorithms, self-preferencing can distort competition, reduce consumer choice, and stifle innovation.

61. This segment examines the economic rationale and competitive implications of self-preferencing in digital markets. It reviews landmark decisions by the European Commission and the Competition Commission of India (CCI) against Google, which highlight how SP practices can amount to abuse of dominance. The paper concludes with policy considerations for competition authorities dealing with the evolving digital economy.

62. Over the past decade, digital markets have become central to global commerce. Firms such as Google, Amazon, and Meta have achieved structural dominance in respective markets search engines, e-commerce, and social media respectively and due to unique features such as network effects, data dependency, and economies of scale. These characteristics amplify the risk that SP can entrench dominance and foreclose competitors.

6.2.1. Understanding Self-Preferencing

63. Self-preferencing occurs when a vertically integrated platform favours its own services over those of rivals. The European Commission defines SP as "the practice of giving preferential treatment to one's own products or services when they compete with those of third parties using the platform".[30]

64. Examples include:

- Amazon promoting its *Amazon Basics* products over third-party sellers.
- Google displaying its own shopping or travel comparison services more prominently in search results.
- Apple preinstalling proprietary apps such as Safari or Apple Music on iPhones.
- Microsoft bundling Internet Explorer and other proprietary software with Windows.

65. While such practices can sometimes yield efficiencies, such as reduced transaction costs or enhanced consumer experience, they may also confer an unfair advantage when employed by dominant firms. The core competition concern arises when a platform leverages dominance in one market (e.g., search) to favour its own services in another (e.g., shopping, payments, or maps).

[30] Carugati, Christophe. *How to Implement the Self-Preferencing Ban in the European Union's Digital Markets Act*. Policy Contribution 22/2022. Bruegel, December 2022.

6.2.2. Self-Preferencing: Competition Law concern

a. Dual Role of Platforms

66. Large platforms act simultaneously as *gatekeepers* and *competitors*. They control access to essential digital infrastructure (e.g., app stores or search engines) while also competing with firms that rely on them. This duality creates a "conflict of interest," allowing platforms to exploit their control over visibility, data, and algorithms to marginalize competitors.

b. Barriers to Entry and Innovation

67. When a dominant platform prioritizes its own services, third-party providers face reduced visibility and traffic. Over time, this leads to reduced investment incentives for smaller firms, weakening innovation ecosystems. Moreover, because platforms often collect and analyse data from dependent businesses, they can replicate popular products effectively "copying to compete", a phenomenon extensively reported in relation to Amazon's marketplace practices.[31]

c. Consumer Harm

68. Self-preferencing can indirectly harm consumers by reducing choice and limiting innovation. Although some argue that lower prices offered by platform-owned brands benefit consumers, the longer-term effect may be market foreclosure and reduced diversity of products and ideas.

6.2.3. Case Analysis: The Google Experience

European Union – Google Shopping Case

69. In 2017, the European Commission fined Google €2.42 billion for abusing its dominant position in general search services by giving preferential treatment to its comparison-shopping service, Google Shopping, while demoting rival services[32] (European Commission Decision, 2017).

70. The Commission found that:

- Google systematically positioned its comparison-shopping results at the top of the search engine results page (SERP), displaying them in a richer, more attractive format.
- Competing services appeared only in text-based results and were subject to algorithmic demotion.
- This conduct diverted traffic from rival comparison sites to Google's own service, consolidating its market power both in general search and in comparison-shopping markets.

[31] Aditya Kalra & Steve Stecklow, *Amazon Copied Products and Rigged Search Results to Promote Its Own Brands, Documents Show*, Reuters (Oct. 13, 2021), https://www.reuters.com/investigates/special-report/amazon-india-rigging/.

[32] Commission Decision of June 27, 2017, Case AT.39740 – Google Search (Shopping), 2017 O.J. (C 9) 8 (EU).

71. The General Court of the European Union (2021) upheld this decision[33] , confirming that *self-preferencing can, in certain circumstances, constitute a standalone abuse of dominance*. The Court emphasized that such conduct must (1) have actual or potential anticompetitive effects and (2) depart from competition on the merits.

72. This case set a global precedent, influencing the Digital Markets Act (DMA) of the EU, which now explicitly prohibits gatekeepers from favouring their own services over third-party offerings.

6.2.4. India – Competition Commission of India's Cases against Google

a. Matrimony.com Ltd. & CUTS v. Google LLC[34] (2018)

73. In this landmark decision , the CCI found Google guilty of abusing its dominance in the market for online general search and search advertising in India. The Commission observed that:

- Google's "universal results" were displayed in fixed positions on the SERP, irrespective of relevance.
- Google prominently displayed its own specialized services such as *Google Flights* and *Google Maps*.
- These practices diverted user traffic to Google's verticals while disadvantaging competitors.

74. The CCI imposed a fine of INR 135 crore and directed Google to ensure non-discriminatory treatment in its search display. The decision underscored that a dominant entity in digital markets bears *special responsibility* not to distort competition.

b. Umar Javeed & Ors. v. Google LLC (2022)[35]

75. In another major decision , the CCI found that Google abused its dominance through mandatory pre-installation of Google Mobile Services (GMS) on Android devices. The agreements—Mobile Application Distribution Agreement (MADA) and Anti-Fragmentation Agreement (AFA)—required smartphone manufacturers to preinstall Google's suite of apps and disallowed their removal.

76. The CCI held that:

- The bundling of apps such as Chrome, YouTube, and Gmail constituted an *unfair condition* under Section 4(2)(a)(i) of the Competition Act, 2002.
- Google leveraged its dominance in the Android OS market to protect its position in general search and non-OS-specific web browser markets.
- The Commission imposed a fine of INR 1,337.76 crore and issued a comprehensive set of behavioural remedies, including allowing users to choose default search engines and permitting uninstallation of pre-installed apps.

[33] *Google v. Commission*, Case T-612/17, EU:T:2021:770 (Nov. 10, 2021).

[34] CCI Case No. 07 & 30 of 2012

[35] CCI Case No. 39 of 2018

c. XYZ v. Alphabet Inc[36]*. (Google Pay Case, 2023)*

77. In this case, the informant alleged that Google favoured its payment service, Google Pay (GPay), by granting it default placement and search prominence within the Play Store. It was argued that such preferential treatment restricted market access for competing UPI apps like Paytm and PhonePe.

78. While the CCI dismissed some allegations for lack of evidence, it ordered an investigation into:

- Exclusive use of Google's payment system for in-app purchases; and
- Pre-installation and default prominence of GPay on Android devices.

79. The case highlights how SP practices can extend beyond search and app bundling into the fast-growing fintech sector, where platform control over payment gateways can influence user adoption patterns.

80. Self-preferencing represents one of the most pressing competition challenges of the digital age. It highlights how traditional antitrust tools must evolve to address the hybrid role of digital platforms as both regulators of market access and active competitors. The EU's and India's enforcement actions against Google mark significant progress in establishing accountability and setting precedent for digital market regulation.

81. However, given the speed of technological change and the scale of digital integration, reactive enforcement may no longer suffice. CCI is moving towards proactive, principle-based and balanced regulation that promotes *contestability, transparency, and fairness* in digital ecosystems.

6.3. AI driven Resale Price Maintenance

82. AI and algorithmic pricing have fundamentally transformed how resale price maintenance (RPM) operates in digital downstream markets. Traditionally, RPM was a contractual mechanism through which manufacturers set a minimum or fixed resale price for their distributors or retailers, often justified on efficiency grounds but condemned where it restricted price competition. However, in AI-driven markets, RPM no longer requires explicit coordination; algorithmic monitoring and data-driven interventions can achieve similar outcomes with greater precision and scale.

83. This segment examines the implications of AI-driven RPM for competition enforcement, using evidence from the European Commission's cases against major electronics manufacturers, the U.K. Competition and Markets Authority (CMA), and emerging Indian perspectives. It highlights the growing risk of algorithmic tools amplifying vertical restraints and the challenges authorities face in detecting and attributing liability.

6.3.1. RPM in digital markets

84. Vertical restraints are the agreements between firms operating at different levels of the supply chain that have long been a core focus of competition law. Among these, resale price maintenance (RPM) is particularly contentious because it constrains the freedom of downstream retailers to determine resale prices.

[36] CCI Case No. 07 of 2020

85. In traditional brick-and-mortar markets, vertical relationships followed predictable patterns: manufacturers supplied wholesalers and retailers, who then determined their own prices and inventory based on demand. Human discretion, local market knowledge, and limited information flows defined the system. Enforcement of RPM was often traceable through contracts, communications, or pricing patterns.

86. In contrast, digital markets operate on algorithmic precision and data-driven responsiveness. Online retailers deploy pricing software that adjusts prices within seconds, responding automatically to competitors' moves, consumer demand fluctuations, and even manufacturer-imposed constraints. This automated environment challenges regulators' ability to distinguish legitimate efficiency-enhancing pricing tools from algorithmically enforced RPM.

87. As Ann Pope, Senior Director at the CMA, aptly observed, "Price competition from online sales is usually intense, given the ease of searching on the Internet. RPM, by preventing retailers from offering discounted prices, denies buyers the benefit of lower prices and the quality improvements that come from genuine competition." This insight encapsulates the central policy dilemma while AI enhances pricing efficiency, it may simultaneously harden price rigidity and undermine consumer welfare.

6.3.2. The Economics of RPM in the Age of AI

88. Traditionally, RPM could be justified on efficiency grounds: it prevented free-riding on retailer services, ensured brand uniformity, or encouraged retailers to invest in pre-sale services. However, when applied indiscriminately, RPM suppressed price competition, limited consumer choice, and facilitated collusion.

89. AI and big data have redefined the parameters of this debate. Algorithms enable real-time monitoring of downstream prices, allowing manufacturers to identify deviations from agreed pricing almost instantly. Unlike conventional monitoring, which required periodic reporting or human oversight, algorithms can detect and respond to pricing behaviour continuously and autonomously.

90. According to surveys from the European Commission's E-commerce Sector Inquiry (2017)[37],

- 53% of online retailers track competitors' prices,
- 67% of these do so automatically using price-tracking software, and
- 78% adjust their prices algorithmically in response to competitors.

91. This extensive use of algorithmic monitoring creates an environment in which price uniformity emerges as a by-product of efficiency, blurring the line between competitive interdependence and collusive restraint. Jullien and Rey (2001)[38] noted that RPM can yield more uniform prices by making deviations easier to detect, a phenomenon that AI now amplifies exponentially.

[37] *European Commission, Commission Staff Working Document Accompanying the Document Report from the Commission to the Council and the European Parliament: Final Report on the E-commerce Sector Inquiry*, SWD/2017/0154 final, 2017 O.J. (C 154) 1 (EU).

[38] Jullien, Bruno & Rey, Patrick, *Resale Price Maintenance and Collusion*, CEPR Discussion Paper No. 2553 (2001).

92. AI also enhances manufacturers' ability to control the pricing chain. In e-commerce ecosystems, suppliers can monitor retailer prices using integrated dashboards, threaten supply limitations, or offer financial incentives to maintain certain price levels. These algorithmic interventions can reinforce vertical control without explicit agreements making traditional legal tests for RPM under competition law less straightforward to apply.

6.3.3. Enforcement Experience and Global Developments

The European Commission's Approach

93. In 2018, the European Commission sanctioned four electronics manufacturers- Asus, Denon & Marantz, Philips, and Pioneer for engaging in RPM through online channels. The Commission found that these firms monitored resale prices of online retailers and intervened when prices fell below agreed thresholds.

94. Crucially, the Commission emphasized that price monitoring and adjustment software amplified the impact of these restrictions. Algorithms enabled manufacturers to track deviations in real-time and exert pressure on retailers to align with fixed prices. The decision established that algorithmic facilitation does not change the legal nature of RPM it remains a hardcore restriction under Article 101 TFEU.

95. The case set an important precedent: enforcement must now account not only for explicit contractual RPM but also for AI-enabled "functional equivalence" where automated systems replicate the anticompetitive effects of traditional RPM without overt communication.

The Indian Context

96. India's digital retail landscape is characterized by hybrid models combining platform sales and third-party vendors that presents unique challenges. The Competition Commission of India (CCI) has yet to adjudicate a major RPM case involving AI-enabled monitoring, but sectoral observations and advocacy initiatives signal awareness of emerging risks.

97. Given the high penetration of algorithmic tools among e-commerce operators, the CCI could benefit from deploying AI-driven investigative tools. This would enhance its ability to detect suspicious vertical restraints in real time.

98. Moreover, Indian competition regulator has recently released the market study on AI and competition and is progressively acknowledging the role of data and AI in shaping competitive dynamics. Integrating algorithmic accountability provisions within this framework could strengthen deterrence and align India with OECD best practices.

6.4. AI-Driven Price Discrimination in Downstream Markets

99. The Organisation for Economic Co-operation and Development (OECD), through its 2016 Roundtable on Price Discrimination[39] and study on AI, data and competition[40], has recognised that algorithmic pricing can enhance market efficiency but may also distort competitive neutrality, facilitate exclusionary strategies, and exploit consumers through opaque and automated discrimination. This segment examines the implications of AI-enabled price discrimination from economic and legal perspectives, with comparative insights from the European Union, the United States, and India, and concludes with policy suggestions for regulating algorithmic pricing in downstream markets.

6.4.1. Economic Rationale and Evolution of Price Discrimination

100. Economically, price discrimination occurs when identical goods are sold to different buyers at different prices, unrelated to cost differences. As Richard Posner notes, it involves selling "the same product to different customers at different prices even though the cost of sale is the same," while Stigler defines it as a divergence between the ratio of prices and marginal costs[41].

101. Three classical forms exist:

1. First-degree (perfect) discrimination: Prices are individually set according to each consumer's willingness to pay.
2. Second-degree discrimination: Prices vary by quantity or purchase conditions (e.g., bulk discounts, premium bundles).
3. Third-degree discrimination: Prices vary across identifiable consumer groups with different demand elasticities (e.g., student discounts or location-based pricing).

102. AI and big data blur these distinctions by making first-degree discrimination operationally feasible. Through predictive analytics, machine learning models can estimate a consumer's willingness to pay based on search history, location, device type, and purchasing behaviour. In effect, algorithms have transformed imperfect market segmentation into precise individual targeting, amplifying both efficiency and fairness concerns.

Legal Approaches: Comparative Perspectives

(a) European Union

103. Article 102(c) of the Treaty on the Functioning of the European Union (TFEU) defines price discrimination as "applying dissimilar conditions to equivalent transactions with other trading parties, thereby placing them at a competitive disadvantage."

[39] Organisation for Economic Co-operation and Development. (2016). *DAF/COMP/M(2016)2/ANN5/FINAL*. Retrieved from https://one.oecd.org/document/DAF/COMP/M(2016)2/ANN5/FINAL/en/pdf

[40] Organisation for Economic Co-operation and Development. (2024). *AI, Data and Competition* (OECD AI Papers No. 18). OECD Publishing. Retrieved from https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf

[41] GEORGE JOSEPH STIGLER, THE THEORY OF PRICE, (Macmillan Company, 1987)

EU enforcement has primarily addressed B2B discrimination by dominant firms where dissimilar pricing harms downstream rivals rather than direct consumer exploitation.

104. The United Brands judgment (1978)[42] established that equivalent transactions must be assessed in their full commercial and legal context, and dissimilar prices must create a competitive disadvantage. Subsequent cases, including British Airways (2007)[43] and MEO (2018)[44], refined the standard toward an effects-based analysis, requiring proof that the discriminatory pricing is capable of negatively affecting the competitive position of the disfavoured party.
The MEO ruling in particular marked a shift from a form-based to an effect-based approach, increasing the burden on competition authorities to demonstrate harm to competition rather than mere price disparity.

105. In digital contexts, the European Commission has tended to focus on exclusionary effects for example, in cases involving online platforms offering differentiated ranking, visibility, or commission structures. Distinctions between “basic” and “upgraded” services are recognised as legitimate forms of product differentiation rather than discriminatory conduct. Direct consumer-facing price discrimination (exploitative abuse) remains rarely prosecuted, reflecting enforcement conservatism toward dynamic pricing in online markets.

(b) United States

106. The U.S. approach to price discrimination evolved under the Robinson–Patman Act of 1936, enacted to protect small retailers against discriminatory pricing by large chain stores. However, contemporary U.S. antitrust law guided by the Sherman Act and modern Chicago School economics largely treats price discrimination as lawful absent exclusionary intent.

107. In Verizon v. Trinko (2004)[45] and Pacific Bell v. linkLine (2009)[46], the Supreme Court reaffirmed that “the mere possession of monopoly power and the concomitant charging of monopoly prices is not unlawful.” U.S. policy thus privileges innovation and efficiency, permitting even significant price disparities so long as they do not foreclose rivals or constitute predatory conduct. Exploitative pricing is not, in itself, an antitrust violation.

108. While algorithmic discrimination has raised new concerns—particularly around consumer deception, bias, and opacity, U.S. agencies such as the Federal Trade Commission (FTC) have addressed these issues primarily under consumer protection and data transparency frameworks, not antitrust law. The 2023 FTC Staff Report on “Commercial Surveillance and Data Security”[47] highlights that algorithmic pricing may

---

[42] *United Brands Company and United Brands Continentaal BV v. Commission of the European Communities*, Case 27/76, [1978] E.C.R. 207.

[43] *British Airways plc v. Commission of the European Communities*, Case C-95/04 P, [2007] E.C.R. I-2331.

[44] *MEO – Serviços de Comunicações e Multimédia SA v. Autoridade da Concorrência*, Case T-369/17, EU:T:2018:543 (Sept. 20, 2018).

[45] *Verizon Communications Inc. v. Law Offices of Curtis V. Trinko, LLP*, 540 U.S. 398 (2004).

[46] *Pacific Bell Telephone Co. v. LinkLine Communications, Inc.*, 555 U.S. 438 (2009).

[47] Federal Trade Commission, *2023 Privacy and Data Security Update* (Mar. 21, 2024), https://www.ftc.gov/system/files/ftc_gov/pdf/2024.03.21-PrivacyandDataSecurityUpdate-508.pdf

constitute an “unfair or deceptive practice” if it uses sensitive or protected attributes without disclosure.

(c) India

109. India’s Competition Act, 2002, under Section 4(2)(a), prohibits a dominant enterprise from “directly or indirectly imposing unfair or discriminatory conditions or prices.” The law incorporates a rule of reason exemption, allowing discriminatory pricing “to meet competition.” Thus, price differentiation is not per se illegal; it must result in demonstrable harm to competition or consumers.

110. Indian enforcement has primarily targeted exclusionary discrimination in B2B contexts. In Grasim Industries (2018)[48], discriminatory discount structures in the viscose staple fibre market were deemed anticompetitive as they distorted the downstream yarn market.B2C algorithmic discrimination, as alleged in Samir Agarwal v. Ola and Uber (2020)[49]was dismissed on the ground that neither platform was dominant. Subsequent government intervention addressed dynamic pricing through sectoral regulation rather than competition enforcement, capping surge prices under the Motor Vehicles Act (2020).

111. These cases reveal that while Indian law formally recognises discriminatory pricing as abuse, enforcement remains limited to traditional dominance cases, leaving algorithmic exploitation largely unaddressed.

6.4.2. The Digital Shift: Algorithmic and AI-Driven Price Discrimination

From Segmentation to Personalisation

112. Digital markets have transformed price discrimination from static segmentation into real-time personalisation. Algorithms aggregate and process behavioural, locational, and transactional data to predict willingness to pay with high accuracy. AI’s predictive capacity allows firms to implement continuous micro-pricing across millions of transactions, a practice already observed in e-commerce, travel platforms, and online services.

113. Empirical evidence shows widespread experimentation with algorithmic pricing:

- Amazon (2000)[50] tested DVD price variations by user profile, prompting consumer backlash.
- Orbitz (2012)[51] showed higher-priced hotels to Mac users, based on data that they spent 30% more per night.

[48]CCI Case No. 51, 54 and 56 of 2017.

[49] CCI Case No.96 of 2015.

[50] James Bates, *Amazon Pays a Price for Marketing Test*, L.A. TIMES (Oct. 2, 2000), https://www.latimes.com/archives/la-xpm-2000-oct-02-fi-30029-story.html (last visited Oct. 22, 2025).

[51] Alex Williams, *Orbitz Shows Higher Prices to Mac Users*, TIME (Jun. 26, 2012), https://business.time.com/2012/06/26/orbitz-shows-higher-prices-to-mac-users/ (last visited Oct. 22, 2025).

- McAfee (2013)[52] offered higher renewal prices to existing customers than to new users.
- Tinder (2019)[53] charged older users twice as much for premium subscriptions, leading to a USD 11.5 million settlement.
- Chinese ride-hailing platforms have been found to adjust fares based on users' device type and historical spending patterns.[54]

114. Such examples illustrate how algorithmic discrimination may evolve into "digital redlining," where consumers are differentially treated based on inferred socioeconomic or demographic traits, often without awareness or recourse.

Empirical and Behavioural Evidence

115. Studies cited by the OECD and academic literature underscore the magnitude of potential harm. Benjamin Shiller (2014)[55] demonstrated that Netflix could increase profits by 12% and reduce consumer surplus by 8% using web-browsing data to predict subscription likelihoods. The Austrian Chamber of Labour (2017) documented significant cross-device and cross-location price variations for identical products on major e-commerce platforms.[56]

116. Behavioural research also indicates that repeat consumers often face higher prices than first-time buyers contrary to loyalty-based expectations due to algorithmic learning that associates repeat usage with higher willingness to pay. This "loyalty penalty" undermines consumer trust and distorts competitive neutrality among digital intermediaries.

Exploitative and Exclusionary Dimensions

117. Algorithmic discrimination can create both exploitative and exclusionary effects:

- Exploitative harm: Consumers are charged the maximum price they can bear, eliminating surplus and potentially leading to regressive outcomes if the algorithm correlates willingness to pay with income, location, or race.
- Exclusionary harm: Rivals may be foreclosed if dominant platforms use discriminatory pricing to favour affiliated sellers or distort search rankings.

---

[52] George Leopold, *McAfee to Change Terms of Auto-Renewing Consumer Plans*, COMPUTER WEEKLY (May 25, 2021),https://www.computerweekly.com/news/252501337/McAfee-to-change-terms-of-auto-renewing-consumer-plans (last visited Oct. 22, 2025).

[53] *Allison v. Tinder, Inc.*, No. 19-55807, 2021 WL 3560755 (9th Cir. Aug. 17, 2021).

[54] Jonathan Wang, *Researchers Took Over 800 Trips Using Chinese Ride-Hailing Apps—Here's What They Found*, KRASIA (May 13, 2021), https://kr-asia.com/researchers-took-over-800-trips-using-chinese-ride-hailing-apps-heres-what-they-found (last visited Oct. 22, 2025).

[55] Benjamin Reed Shiller, *First-Degree Price Discrimination Using Big Data*, Brandeis Univ. Econ. Dep't, Working Paper No. WP58R2 (Jan. 6, 2014), https://www.brandeis.edu/economics/RePEc/brd/doc/Brandeis_WP58R2.pdf.

[56] Organisation for Economic Co-operation and Development, *Annual Report on Competition Policy Developments in Austria*, DAF/COMP/AR(2017)1 (June 29, 2017), https://one.oecd.org/document/DAF/COMP/AR(2017)1/en/pdf..

118. Moreover, algorithmic opacity complicates detection. Self-learning models may autonomously generate discriminatory outcomes even without explicit human intent. OECD's 2023 "Competition in the Age of AI" report cautions that such autonomous decision-making may warrant scrutiny under both competition and consumer protection frameworks.

119. The evolution of price discrimination from manual to algorithmic represents both a technological triumph and a regulatory challenge. As markets become increasingly data-driven, competition authorities must adapt from analysing static prices to understanding dynamic, self-learning systems. The OECD's role in fostering coherence, transparency, and fairness across jurisdictions will be crucial.

120. AI-driven pricing may increase overall efficiency, but unchecked, it risks transforming competitive markets into personalised monopolies. Ensuring that AI serves consumers and not exploits them should remain at the heart of policy design in downstream digital markets.

7. Enforcement Challenges

7.1. Evidentiary Barriers

121. Traditional competition law frameworks—developed for tangible goods and static markets—struggle to assess algorithmic pricing. Establishing "equivalent transactions" or proving "competitive disadvantage" becomes highly complex when algorithms customise each price. The evidence of intent or coordination is often unavailable, and causality between data-driven pricing and market harm remains difficult to quantify.

7.2. Transparency and Information Asymmetry

122. Consumers are rarely informed when prices are personalised. Even when disclosed, the complexity of algorithmic systems renders meaningful consent illusory. As OECD's 2022 consumer policy guidance notes, "transparency without comprehension does not ensure fairness." Regulators face the dual challenge of mandating algorithmic accountability while preserving innovation.

7.3. Jurisdictional and Institutional Constraints

123. Competition authorities often lack technical expertise to audit algorithms or interpret large-scale data systems. The boundaries between competition, data protection, and consumer law blur, requiring cross-sectoral cooperation. Moreover, differing legal traditions consumer welfare in the EU, total welfare in the U.S. lead to divergent enforcement thresholds, complicating global coordination.

124. This graduated model aligns with OECD's 2024 Competition Toolkit on AI[57], which emphasises proportionality and evidence-based intervention.

[57] Organisation for Economic Co-operation and Development, *AI, Data and Competition*, DAF/COMP(2024)2 (May 6, 2024), https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf

8. Conclusion and Policy Recommendations

125. AI and big data have transformed price discrimination from a theoretical concern into a real and pervasive feature of digital markets. The capacity of algorithms to extract individual willingness to pay challenges the traditional balance between efficiency, innovation, and fairness. While some degree of personalised pricing may enhance total welfare, opaque and exploitative uses threaten consumer trust and competitive neutrality.

126. The tension between ex-ante and ex-post competition regulation is increasingly evident in AI-driven downstream markets, where data access and algorithmic advantages can quickly entrench dominance. India's Competition Act, 2002 adopts an ex-post approach, allowing the Competition Commission of India (CCI) to intervene after anti-competitive conduct occurs. However, this may not be sufficient in fast-evolving digital markets. To address these challenges, India had previously proposed the *Digital Competition Bill, 2024,* introducing ex-ante obligations for Systemically Significant Digital Enterprises (SSDEs)- a model comparable to the European Union's Digital Markets Act (2022) and the United Kingdom's Digital Markets, Competition and Consumers Act (2024). At the same time, India's Competition Commission (Settlement and Commitment) Regulations, 2024[58] offer a hybrid mechanism that allows parties to settle or commit to behavioural changes during investigations. This model blends preventive and corrective regulation, enabling quicker resolution and encouraging compliance without lengthy litigation. Supporters argue that such a combination of ex-ante duties and negotiated remedies can effectively manage risks in AI-driven markets, while critics caution against over-regulation and uncertainty for emerging firms.

127. Alternatively, a U.S.-style dispute resolution mechanism could be adopted, allowing participation of representatives from all affected market participants to resolve issues collaboratively. This approach can address market-wide problems without the need for prolonged investigations. It is suggested that CCI employ this mechanism on a case-by-case basis, only where an amicable solution is feasible, ensuring efficiency while safeguarding fair competition and innovation. Such a combination of ex-ante duties and negotiated remedies can effectively manage risks in AI-driven markets, while critics caution against over-regulation and uncertainty for emerging firms. The ongoing task is to calibrate these tools to ensure fair competition, innovation, and consumer welfare in rapidly changing digital ecosystems.

8.1. Policy Recommendations

8.1.1. Policy recommendations for regulators

128. As AI increasingly drives pricing, market structuring, and consumer targeting in digital platforms, competition authorities face a dual challenge: harnessing the efficiency potential of AI while preventing anti-competitive behaviour and protecting consumer welfare. Traditional regulatory tools often struggle to keep pace with algorithmic complexity, opacity, and speed. To navigate these challenges, we propose a set of policy recommendations that combine transparency, enforcement, capacity-building, and consumer empowerment.

[58] Competition Commission of India. (n.d.). *Regulations.* https://www.cci.gov.in/legal-framwork/regulations

1. Strengthen Algorithmic Transparency and Auditability:

129. The foundation of effective oversight lies in making AI-driven pricing decisions understandable and accountable. Firms should maintain detailed algorithmic audit trails that document data inputs, training parameters, and intervention logs. Such records allow regulators to detect collusion, discriminatory pricing, or exclusionary strategies. To protect proprietary technology, confidential disclosure frameworks can enable regulators to inspect algorithms without risking intellectual property theft. Additionally, the adoption of explainable AI (XAI) standards ensures that pricing systems affecting consumer markets are interpretable, enhancing accountability and trust. Transparency here is not a bureaucratic hurdle, it is essential for ensuring fairness in AI-mediated markets.

2. Deploy RegTech Tools for Detection and Analysis:

130. Transparency must be complemented by proactive monitoring. AI-powered surveillance systems can identify anomalous pricing patterns or suspicious market behaviour, enabling regulators to intervene before harm escalates. Authorities should invest in capacity-building initiatives and joint technological projects under forums such as the OECD's Global Competition Forum to share expertise and tools across borders. Collaboration with academic institutions can further support modelling algorithmic pricing networks and simulating potential resale price maintenance effects, helping regulators anticipate market outcomes rather than react post-factum. Such tools are critical for modern oversight in digital markets where manual monitoring is insufficient.

3. Issue Updated Guidance on Vertical Restraints in Digital Markets:

131. Existing doctrines like RPM must be reinterpreted in light of AI-mediated pricing. Authorities should clarify that automated monitoring or dynamic pricing used to enforce fixed resale prices remains per se illegal in jurisdictions adopting strict rule-based approaches. Joint guidance from OECD and national regulators can help e-commerce operators understand how traditional rules apply to algorithmic systems. Promoting self-assessment mechanisms and compliance templates encourages proactive adherence, reducing the risk of violations while supporting innovation.

4. Foster Cross-Border Cooperation and Data Sharing:

132. Digital platforms operate globally, making enforcement of AI-related anti-competitive conduct inherently multi-jurisdictional. Regulators should promote mutual recognition of digital evidence and develop standardized data exchange protocols for algorithmic audit findings. Collaborative enforcement in cases involving multi-jurisdictional e-commerce platforms ensures no regulatory gaps exist, creating a level playing field for consumers and businesses alike.

5. Establishing Guidelines for Digital Market Assessment in India:

133. In the context of the rapidly growing digital economy in India, there is a clear need for a balanced policy framework for assessing market conduct. Soft approaches, such as self-regulation, have proven largely ineffective without adequate regulatory oversight. For instance, the e-commerce report[59] published by CCI recommended for self-regulation by platforms; however, in practice, compliance has been minimal or non-existent.

[59] Competition Comm'n of India, Market Study on E-Commerce in India: Key Findings and Observations (2020), https://www.cci.gov.in/images/marketstudie/en/market-study-on-e-commerce-in-india-key-findings-and-observations1653547672.pdf.

134. At the same time, adopting a very stringent approach, similar to the EU's DMA, may not be appropriate in India. Such rigid regulatory measures could stifle innovation and slow the growth of digital markets, which are currently witnessing exponential expansion.

135. To address this challenge, the CCI should issue clear, practical guidelines for digital market assessment. These guidelines would serve as a benchmark for self-assessment by platforms, while also providing a structured basis for regulatory intervention when necessary. This approach strikes a balance between ensuring fair competition and fostering innovation, allowing India's digital markets to grow sustainably while maintaining oversight over potentially anti-competitive practices.

6. Build Institutional and Human Capacity:

136. Regulating AI requires interdisciplinary expertise. Competition authorities must invest in teams that combine economics, data science, and legal analysis, and collaborate across agencies such as data protection and consumer protection authorities. Establishing AI ethics units can help evaluate long-term impacts on consumer autonomy, privacy, and market fairness. By cultivating cross-disciplinary expertise in data science, behavioural economics, and AI ethics, authorities are better positioned to address both immediate and structural challenges of AI-driven markets.

7. Algorithmic Transparency and Audits:

137. Mandatory algorithmic impact assessments (AIAs) can further enhance accountability. Firms deploying dynamic pricing should disclose whether prices are personalized, the key parameters driving pricing decisions, and the use of sensitive or protected data inputs such as race, age, or location. Such measures prevent discriminatory practices and ensure algorithms operate within the bounds of fair competition.

8. Consumer Empowerment and Data Portability:

138. Empowered consumers can counterbalance the asymmetry of information in digital markets. Regulators should promote personalized pricing notifications at the point of sale, the right to explanations for algorithmic decisions, and data portability rights that allow consumers to compare offers across platforms. These measures, aligned with the OECD's 2024 Digital Consumer Policy Principles, restore trust in digital markets and reduce vulnerability to unfair practices.

9. Case for a Calibrated Regulatory Approach:

139. A binary approach to AI-driven price discrimination, either outright prohibition or complete laissez-faire is neither practical nor effective. Authorities must adopt a calibrated framework, balancing efficiency potential with distributional risks. This involves monitoring and soft regulation for non-dominant firms via market studies, voluntary codes, and transparency obligations, alongside targeted enforcement against dominant platforms engaging in exclusionary or exploitative discrimination. Such a nuanced approach preserves innovation incentives while safeguarding consumer welfare and market fairness.

8.1.2. Policy recommendations for OECD

1. Clarify Legal Standards: OECD could promote consistent definitions of algorithmic price discrimination and encourage member states to update abuse of dominance frameworks to address exploitative AI-driven conduct.
2. Mandate Algorithmic Transparency: Require firms to disclose when and how prices are personalised, the categories of data used, and whether sensitive attributes influence pricing.
3. Institutional Capacity Building: Support training and joint task forces between competition, consumer protection, and data regulators to assess algorithmic pricing systems.
4. Develop Empirical Tools: OECD could coordinate the creation of analytical frameworks for estimating consumer surplus loss and total welfare effects in algorithmic markets.
5. Cross-Jurisdictional Cooperation: Establish an OECD-led observatory on “AI and Market Practices” to share case studies, methodologies, and enforcement outcomes among member jurisdictions.
6. Development of assessment models: OECD could encourage development of quantitative assessment models that estimate the welfare effects of algorithmic pricing, integrating behavioural data and distributional impacts. This would aid authorities in balancing innovation incentives with fairness concerns.
7. Disclosure standard for algorithmic pricing: OECD could facilitate harmonisation by defining minimum disclosure standards for algorithmic pricing globally.
8. Establish a technical network on algorithmic enforcement: OECD’s Competition Division could establish a technical network on algorithmic enforcement, pooling expertise from national agencies to share methodologies for algorithm audits and market studies.