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Artificial Intelligence and Competitive Dynamics in Downstream Markets – Background Note

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Artificial intelligence and competitive dynamics in downstream markets

This paper examines how the adoption of artificial intelligence (AI), particularly generative and agentic systems, is reshaping competition in downstream markets. It explores mechanisms through which AI may lower barriers to entry, substitute for labour, reduce minimum efficient scale, and support innovation and product differentiation. At the same time, it highlights emerging risks related to data access, model restrictiveness, and the downsides of AI use.

The paper analyses how AI affects market structure and may shape firm behaviour, finding that its competitive impact is highly context-dependent, shaped by sectoral exposure to AI use, firm size and capabilities, and access to enabling inputs. It concludes by discussing enforcement, advocacy, and regulatory tools that may help preserve contestability, and identifies areas for future research, including attribution of liability and the implications of agentic AI systems. The analysis is intended to support competition authorities in navigating AI-related market developments.

Key words: Agentic AI, Algorithmic collusion, Artificial Intelligence, Barriers to entry, Competition enforcement in AI, Data access, Efficiency and productivity gains, Generative AI, Market contestability, Price discrimination, Sector uptake of AI

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Executive summary

This paper examines how the adoption of artificial intelligence (AI), particularly generative and agentic systems, is reshaping competition in downstream markets. While much of the policy debate has focused on competition in AI infrastructure and foundation model development, this paper considers how AI is used as an input into production, service delivery, logistics and customer engagement.

The analysis suggests that AI may support competition in downstream markets by lowering barriers to entry, reducing minimum efficient scale, and enabling product differentiation and innovation. At the same time, it identifies emerging risks related to data access, model restrictiveness, vertical integration and algorithmic conduct. The paper does not aim to provide an exhaustive sectoral review, but rather to highlight mechanisms and conditions that may support or hinder competition in AI-enabled markets.

AI as a general-purpose technology

Generative AI (GenAI) exhibits characteristics of a general-purpose technology, including pervasiveness, continuous improvement and innovation-spawning potential. Estimates of productivity gains vary, with studies suggesting annual increases in total factor productivity (TFP) ranging from 0.07 to 1.3 percentage points. However, the diffusion of AI remains uneven across sectors and firms, raising concern of an emerging AI-divide.

Mechanisms supporting competition

AI adoption may foster competition through several channels:

Labour substitution and augmentation: GenAI systems can automate cognitive tasks, particularly routine or repetitive tasks, lowering the skills threshold for market participation. Field experiments also suggest significant productivity gains, particularly for less experienced workers when they use AI to help perform higher-skilled tasks. This may reduce entry barriers in knowledge-intensive sectors by enabling smaller teams to perform functions that previously required larger, highly skilled workforces, supporting leaner and more agile business models.

Product improvement and innovation: AI can enable mass customisation and personalised services, supporting differentiation. Smaller firms can access design and communication tools previously reserved for larger incumbents. This expands the range of viable business models and opens space for challengers to compete on quality, user experience and new product features, rather than solely on scale.

Cost reduction, efficiency and productivity gains: AI adoption can reduce operating costs through automation, predictive analytics and modular deployment, which may lower fixed costs and support incremental scaling. At the same time, empirical studies report productivity gains in the form of time savings and quality improvements across a range of professional tasks. Taken together, these effects can enable leaner business models and facilitate entry into markets that might previously have been inaccessible.

Reduced search and switching costs: AI can also promote competition in downstream markets by reducing consumers' search and verification costs. AI-enabled search, recommender and conversational systems help filter, rank and personalise options, which can broaden effective choice sets, improve matching efficiency and intensify competitive pressure on price and quality. Theoretical and empirical work shows that these systems save time and reduce effort, drawing in previously inactive consumers and enabling more efficient comparison across alternatives.

These benefits may not be evenly distributed as the competitive effects are highly context dependent. Adoption costs, integration challenges and access to enabling inputs such as data and compute may limit uptake, particularly among smaller firms. Moreover, some sectors remain less exposed to AI, and certain tasks may not be easily automated. Data access and the conditions under which firms can use or adapt AI models also influence competition both upstream and downstream. While concentrated control of data and cloud infrastructure may create advantages for large providers, widespread access to interoperable models and the ability to fine-tune them can support differentiation and entry. The competitive implications therefore depend on access terms, portability, and the practical ability of firms – particularly smaller ones – to tailor and integrate AI into their operations.

Furthermore, the pro-competitive effects of reduced search costs may depend on system design: if ranking or recommendation processes lack transparency or embed biases, they may channel demand towards particular suppliers and limit contestability. Ensuring fair visibility and portability across intermediaries is therefore central to realising these benefits.

Emerging risks, limits and competition concerns

The paper highlights potential downsides of AI adoption, such as homogenisation of outputs and reduced creative diversity, security vulnerabilities and quality control challenges, and sectoral divides, with professional services and ICT showing higher uptake than manual or in-person service sectors. The concept of an “AI divide” is emerging, with advanced economies, and larger firms better positioned to absorb upfront costs and integrate AI into workflows, and some emerging markets, or firms that lack access to compute and talent. Larger firms may also be able to acquire potential emerging competitors. This may reinforce incumbency and limit contestability.

Potential competition concerns

The paper also outlines both traditional and emerging competition concerns that may arise from the downstream use of AI systems by firms:

- **Horizontal co-ordination**: AI may facilitate algorithmic collusion, including hub-and-spoke arrangements and tacit co-ordination. Enforcement challenges include attribution of intent and evidentiary standards.
- **Unilateral conduct**: Dominant firms may use AI to exclude rivals through ranking bias, personalised pricing or bundling. Vertical integration across the AI stack may enable cross-layer leveraging and input foreclosure.
- **Attribution of liability**: Autonomous optimisation complicates enforcement. The paper discusses the need for auditability, transparency and oversight mechanisms to support accountability.
- **Agentic AI and market structure**: A related emerging concern is the development of AI agents and Agentic AI. *AI agents* are systems that can perceive and act on their environment, often autonomously, to achieve specific goals, and can adapt their behaviour in response to changing inputs or contexts (OECD, 2025[1]). *Agentic AI* refers to systems composed of multiple co-ordinated AI agents that can break down tasks, collaborate, use external tools and pursue goals over extended periods with limited human supervision. These systems are designed for more open-ended and less predictable environments, enabling autonomous planning and action across workflows. While still nascent, Agentic AI could reshape competition in markets such as search,

workflow automation and customer engagement. Their integration into cloud and hyperscaler ecosystems may also increase vertical dependencies and raise risks of leveraging or foreclosure, particularly where access to compute, data or distribution becomes strategically controlled.

Conclusion and future directions

AI adoption in downstream markets presents both opportunities and challenges for competition. While AI may lower entry barriers and support innovation, its impact is shaped by access to enabling inputs, market structure and institutional context. The paper suggests that a multi-pronged approach – combining enforcement, advocacy, including market monitoring, regulation and co-operation – may be needed to ensure that AI-enabled markets remain open, pro-competitive and innovation-friendly.

Further empirical research is needed to assess sector-specific impacts, particularly (but not exclusively) in areas such as health, finance, professional services, platform services, search, logistics and creative industries. The rise of agentic AI also warrants close monitoring, given its potential to reshape intermediation and consumer choice.

1 Introduction

1. This paper examines how the adoption of artificial intelligence (AI) by firms in traditional and emerging sectors may affect competition. While much attention has focused on competition in AI infrastructure and foundation model development, the emphasis here is on how AI is used as an *input* into production, service delivery, logistics, and customer engagement. The paper is part of the OECD Horizontal Project on 'Thriving with AI: Empowering Economies, Societies and Citizens' and also contributes to a workstream of OECD "Competition and AI" papers that discuss steps in the AI value-chain, as well as various aspects of competition within the field of AI itself (see notably (OECD, 2024[2]; OECD, 2025[3]; OECD, 2025[4])).

2. AI adoption is heterogeneous across firms and sectors. Productivity effects also vary, with significant gains in professional services and manufacturing, but less in markets that largely rely on manual work and in-person services (Calvino, Reijerink and Samek, 2025[5]) The central question is whether using AI technologies helps lower barriers to entry and promote competition, or conversely may reinforce incumbency through control of data, compute, and ecosystems. AI can allow firms to automate, scale, personalise, and optimise outputs and services, supporting entry and innovation. At the same time, it may facilitate concentration of capability, vertical leveraging by dominant platforms, or new forms of anti-competitive behaviour, including algorithmic collusion.

3. The analysis does not aim to provide an exhaustive account of all sectors. Rather, the aim is to shed light on the factors and mechanics that support or hinder competition in the markets that adopt AI based tools. Given that issues specifically related to AI infrastructure will be addressed in a separate OECD paper (OECD, 2025[4]), this paper refers to them only insofar as they have direct implications for downstream competition.

4. As the topic is as yet under-researched and the sector is incredibly fast-moving, with daily breakthroughs, start-up launches or new uses reported in the media, many examples rely on press-reports or Internet research. Examples cited herein should be taken as illustrative as opposed to authoritative. Taken together, the aim is that these perspectives will contribute to a body of work to help readers better understand in which circumstances the use of AI is likely to be pro-competitive and hence, where regulators should seek to promote or protect its entry and use from vested interests or regulation; or conversely, to understand when the use of AI might be anti-competitive, and hence national competition authorities (NCAs) should be vigilant to protect competition across a wide range of downstream markets.

1.1. Key concepts used

5. This section describes, for the purpose of this paper, several concepts in artificial intelligence (AI) that are central to the analysis of its impact on competition. The terminology is grounded in OECD frameworks, including analytical and policy-oriented publications. The OECD defines an AI system as a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment (OECD Council, 2024[6]). The AI stack (infrastructure, model development and deployment), its technical components as well as the key enablers of compute, data and talent, along with their

competitive impact, have already been extensively analysed in previous OECD competition work (OECD, 2024[2]; 2025[3]), and are therefore taken as given here.

6. **Foundation Models** (FMs) refer to a class of very-large AI systems (often a deep neural network) trained on vast and diverse datasets (often known as *corpora*[1]) using self-supervised learning techniques. They are designed to perform a wide range of general tasks across domains such as language, vision, and speech, and to be general-purpose in nature. FMs can power a variety of downstream applications and underpin many of the most advanced AI systems currently in use, including those used in language processing, image generation, and scientific discovery (OECD, 2024[2]; Calvino, Haerle and Liu, 2025[7]; Zenner, 2023[8]).

7. **Large Language Models** (LLMs) are a prominent type of FMs. They are designed to understand and generate human language, and can perform a wide array of tasks such as summarisation, translation, question answering, and content generation. They are often accessed using chatbot interfaces such as ChatGPT (Open.AI) Claude (Anthropic) and LeChat (Mistral). These interfaces determine how end-users access and benefit from the capabilities of foundation models (OECD, 2023[9]; byby.dev, 2025[10]).

8. **Generative AI (GenAI)** refers to AI systems that are capable of producing novel content, such as text, images, audio, video, or code, based on patterns learned from training data. The GenAI sector can be broadly divided into two segments: upstream, where foundation models are developed, and downstream, where specialised models are built from FMs. Developers may decide (i) to vertically integrate their foundation models with downstream AI services, (ii) to provide access to third-party developers, (iii) and the level of access they give to their models. Access to FMs is often granted via cloud services, which may in turn vertically integrate with specialised models, or provide services to third-party developers. The extent to which a FM is vertically integrated or made accessible to cloud providers or to third-party developers is the result of a strategic decision made by the FM developer (AdC, 2024[11]).

9. GenAI has been described as a **general-purpose technology**. With characteristics such as pervasiveness, continuous improvement and innovation-spawning potential, it may reshape productivity, innovation, and market structures across a wide range of sectors (Calvino, Haerle and Liu, 2025[7]). As with previous GPTs, such as electricity or the internet, the diffusion of generative AI is expected to be uneven, with significant implications for competition policy, including the risk of market concentration and the advent of new bottlenecks in the AI value chain.

10. Applications built on FMs are typically **fine-tuned** to perform specific tasks or serve particular user groups. It is a distinct and critical phase in the GenAI lifecycle (OECD, 2024[2]) Fine-tuning involves training the model further on domain-specific or firm-specific data to improve performance. For example, enterprise copilots may be fine-tuned on proprietary business data, while consumer chatbots may be adjusted for tone or content moderation. Fine-tuning is key to how GenAI systems are deployed in downstream markets. It influences accessibility, differentiation, and the potential for innovation across sectors.

11. Understanding how AI systems function, is essential for analysing how using AI may affect market entry, firm behaviour, and competitive dynamics. As these technologies evolve, so too will their implications for competition enforcement and policy design. Throughout the paper, the terms "AI-systems", "AI" and "Generative AI (GenAI)" will be used interchangeably and will also sometimes encompass the features of FMs and LLMs. If an example or use case relies on a particular form of AI, this will be specified.[2]

12. The paper is structured as follows: Section 2 examines the uptake of AI across sectors and firms, highlighting both the opportunities for greater efficiency and the barriers that can limit adoption, including access to data and model openness shape, with implications for downstream contestability. Section 3 explores traditional and emerging competition concerns associated with AI systems, including algorithmic collusion and vertical foreclosure, and outlines actions to support competitive dynamics in AI-enabled markets, including enforcement, advocacy, regulation, and co-operation. The paper concludes with reflections on future research directions.

2 The impact of AI adoption on market dynamics

13. As a general-purpose technology, GenAI exhibits defining characteristics such as pervasiveness, continuous improvement over time and innovation spawning, with implications for future productivity growth (Eloundou et al., 2024[12]; Calvino, Haerle and Liu, 2025[7]; Aghion and Bunel, 2024[13]). Estimates of future gains to total factor productivity (TFP) from the use of AI range from a conservative annual increase of 0.07 percentage points (Calvino, Haerle and Liu, 2025[7]), to an estimate of 0.68 pps of additional TFP growth per year (Aghion and Bunel, 2024[13]), to a recent OECD study which finds a range of 0.4-1.3 percentage points in annual TFG growth in countries with high AI exposure, such as the United States (Filippucci et al., 2025[14]). Most of these studies look at expected AI adoption rates by sector and their estimated potential effect on sector productivity, then aggregate to the wider economy. Each study comes with many caveats, not least the expected rate of adoption, and the likely effect on firm or sector productivity.

14. Taking a starting point in this discussion, this chapter focuses on the mechanisms through which AI adoption enables firms to lower costs and increase productivity, thereby reducing barriers to entry and enhancing market contestability. The chapter also explores sector-specific examples and emerging evidence on AI uptake, while noting that the competitive effects of AI depend on its diffusion and integration across industries. The chapter first considers in which ways AI may substitute for labour, lower costs for firms and increase labour productivity, using an emerging empirical literature. The chapter then looks at some of the more negative aspects associated with AI adoption, before moving sector-exposure to AI, to try to gauge its likely adoption. Finally, some surveys on actual surveys on actual AI use are discussed.

2.1. What are the mechanics by which AI can foster competition?

15. Downstream firms that adopt AI may be able to produce outputs and services at lower costs, fewer staff, and higher productivity, while also offering new services, all of which contribute to lowering entry barriers. This section takes a look at these aspects.

2.1.1. Labour substitution

16. GenAI systems are by now able to perform many tasks that used to be reserved for cognitive workers, such as writing, coding, summarising articles, brainstorming ideas, organising plans, translating other languages, writing complex emails, generating images, and much more. These capabilities allow firms to automate or accelerate labour-intensive processes, often without requiring specialised technical skills. Natural Language Processing (NLP) interfaces such as chatbots and voice assistants, enable employees with limited training or qualifications to interact with AI tools to generate code, perform data analysis, or produce professional writing outputs, potentially lowering the skills threshold for market participation (OECD, 2024[2]).[3]. This could potentially allow SMEs or start-ups to enter markets with fewer staff and lower fixed costs.

17. GenAI helps structure and guide less experienced users while complementing the expertise of advanced workers. When used collaboratively in teams to perform group tasks, GenAI improves team performance and supports personalised learning. By automating routine tasks, AI also frees individuals for more complex or creative work, enabling leaner, more agile business models that can challenge established players OECD research finds that the strongest gains from using AI come when GenAI is used to augment human capacities by automating well-defined tasks, as opposed to tasks performed solely by the AI (Calvino, Reijerink and Samek, 2025[5]).

18. In particular, AI systems can substitute for more experienced workers for some tasks, and can also reduce the need for large teams in areas such as customer support, software development, and marketing. These dynamics could lower barriers to entry in knowledge-intensive sectors, where expertise and team size have traditionally conferred competitive advantage (Brynjolfsson, Li and Raymond, 2023[15]; Li et al., 2024[16]; Noy and Zhang, 2023[17]; Peng et al., 2023[18]). Field experiments confirm that less experienced developers achieve disproportionate productivity gains when supported by AI assistants (Cui et al., 2024[19]) (see also Box 1).

Box 1. AI and knowledge worker substitution

Experimental evidence suggests that generative AI systems could potentially alter the landscape of knowledge work by substituting for certain forms of expertise and narrowing performance gaps between workers. In a large-scale field experiment with over 750 consultants at Boston Consulting Group, Dell'Acqua et al. found that access to GPT-4 led to a 12% increase in task completion, a 25% reduction in time spent, and a more than 40% improvement in output quality. However, the largest gains were observed among lower-performing individuals, whose performance improved by 43%, compared to 17% for top performers. These findings suggest that generative AI could potentially substitute for experience, or specialised training, enabling less experienced workers to perform at levels previously associated with more senior staff.

This form of knowledge substitution could have important competitive implications: if deployed at scale it would reduce the need for large, highly skilled teams, lower the cost of entry into knowledge-intensive markets, and allow smaller firms to compete more effectively with incumbents.

The study also identifies emerging collaboration models, the so-called "Centaurs," who strategically divide tasks between humans and AI, and "Cyborgs," who fully integrate AI into their workflows, highlighting how AI can complement rather than replace human capabilities. Within knowledge workers, the use of AI, if fully integrated, could then potentially redistribute competitive advantage in favour of agile, tech-enabled challengers.

Source: Dell'Acqua et al (2023[20]), Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality, http://dx.doi.org/10.2139/ssrn.4573321.

19. AI-enabled tools reduce the minimum efficient scale by allowing smaller teams to perform functions such as customer support, compliance monitoring and demand forecasting that previously required large workforces, thereby lowering entry barriers and enabling incremental scaling with limited upfront investment (Gupta, 2025[21]).[4] In software development, GenAI models capable of generating and debugging code similarly reduce labour intensity and team size requirements. In software development, using coding copilot systems has enabled developers to complete coding tasks up to 55% faster (Peng et al., 2023[18]; Chui et al., 2023[22]). This reduces both the total hours of engineering labour required and the need for large quality-assurance teams. For example, an early-stage software-as-a-service (SaaS) company can release a minimum viable product with only a handful of engineers, whereas historically larger teams would have been required to build and maintain reliable software (InData Labs, 2024[23]). By

cutting operational and engineering costs, AI lowers capital and labour thresholds for market entry, enabling micro-vendors to contest markets traditionally dominated by larger incumbents (Calvino, Reijerink and Samek, 2025[5]). These factors all point to GenAI as an instrument that can increase market competition by reducing the minimum efficient scale of firms, by substituting the AI systems for some of the required labour force.

20. The underlying assumption that GenAI is cheaper than human labour will depend on cost structures related to usage models and billing arrangements, as well as the sector and tasks where the AI systems are deployed. From a competition perspective, therefore, although the substitution of labour through AI may lower entry barriers by reducing the need for specialised staff and enabling leaner operations, these benefits may not be evenly distributed. The financial and organisational costs of adopting AI may constitute significant barriers, especially for smaller firms and less digitalised sectors. These include high upfront investment requirements (for data infrastructure, computing resources and personnel to handle the AI), integration costs linked to adapting legacy systems, and recurring expenses for cloud services, model fine-tuning and cybersecurity. These costs are not limited to technology acquisition but extend to complementary investments, such as staff training, change management and data governance frameworks (Kergroach and Héritier, 2025[24]). As such, the competitive impact of labour substitution is likely to be heterogeneous, depending on firm capabilities and sectoral conditions.

2.1.2. Product improvement and innovation

21. AI systems may also contribute to a reshaping of competition by enabling new forms of product and service differentiation, and improve service quality. GenAI allows firms to personalise offerings at scale, tailoring content, interfaces, and recommendations to individual users. This works by learning detailed representations of individual users from their behaviour and context, which allows the system to predict what any given user is likely to find useful or engaging. Firms can then dynamically adjust the content, recommendations or interface shown to each user, scaling this personalised adaptation across millions of users at once (Rafieian and Yoganarasimhan, 2023[25]).Firms integrating AI into decision-making report better forecasting and personalised services, improving customer experience, which creating opportunities for challengers to differentiate rather than to compete on scale alone (Krakowski, Luger and Raisch, 2022[26]). This capacity for mass customisation is increasingly accessible to smaller firms using prompt-based tools and multimodal models.

22. In sectors where customer experience and brand identity are key competitive levers, such democratisation of design and communication tools can intensify rivalry and erode incumbents' traditional advantages. It enables new forms of user engagement, product differentiation, and service delivery, with implications for market structure, innovation, and accessibility in downstream markets. AI-generated marketing assets, product imagery, and voice content allow small firms to present professionally branded services without external agencies (Calvino, Haerle and Liu, 2025[7]; OECD, 2024[2]). Over time, AI-generated outputs – cheaper, faster, and often indistinguishable from human-created content – may reshape market dynamics in sectors such as imagery, music, film animation, coding, marketing, translation, and customer services. In these fields, consumer preference for low-cost, high-quality AI content could increase rivalry between AI-enabled entrants and established firms.

23. Integrating AI can also stimulate innovation and research and development (R&D): More than 70% of surveyed enterprises conduct R&D on AI for their own use, and over half collaborate with universities or public research organisations, supporting both innovation and talent acquisition (OECD/BCG/INSEAD, 2025[27]). In pharmaceuticals, AI-driven drug discovery is expected to reduce R&D times, opening opportunities for biotech entrants (OECD/BCG/INSEAD, 2025[27]). In transport, studies of autonomous vehicle fleets in Singapore suggest that AI can expand modal choice and reduce consumer costs when integrated with public transport (Mo et al., 2021[28]).

24. By lowering the cost of prediction, data analysis, optimisation and creative production, AI may enhance competition by enabling new entrants to challenge incumbents with novel offerings and shifting the sources of competitive advantage towards firms that combine domain expertise with AI capabilities (Agrawal, Gans and Goldfarb, 2018[29]; Krakowski, Luger and Raisch, 2022[26]; Gupta, 2025[21]). These capabilities intensify competition and raise incentives for incumbents to innovate (Gupta, 2025[21]).

2.1.3. Cost reduction, efficiency and productivity gains

25. AI adoption can support competition by lowering entry barriers thanks to a reduction of operating costs. This happens through improving information efficiency, automation, task complementarity, and improved error control (Acemoglu, 2024[30]). When firms incorporate AI into their production processes, they incur variable costs for acquiring the necessary software as well as fixed costs for installing AI infrastructure (Maydell, 2024[31]). Costs involved in deploying AI systems include model training, infrastructure, and data integration. However, AI-systems enable task-level cost savings for downstream users, implying that additional tasks can be handled at relatively low marginal cost once systems are deployed (teneo.ai, 2025[32]; Acemoglu, 2024[30]; Korinek, 2024[33]). For example, predictive maintenance systems can monitor thousands of machines simultaneously without proportional increases in labour or analytics costs, enabling firms to expand output and profitability with relatively low incremental cost. (Aggarwal et al., 2021[34]). In health diagnostics, AI models used in clinics can interpret additional scans or tests at negligible extra cost compared to human specialists, whose time and attention scale linearly with workload (McGenity et al., 2024[35]; Aggarwal et al., 2021[34]).

26. AI systems can replicate certain expert tasks (e.g. fault detection, anomaly classification, image interpretation) which traditionally require highly trained personnel. Unlike human experts, automated inference allows scaling through compute rather than labour, reducing the cost of handling additional cases. In manufacturing, AI-based predictive maintenance systems can anticipate failures ahead of time, and thereby sharply lower unplanned downtime and emergency repair costs (e.g. unplanned downtime reductions of up to 70 %, lifecycle extension of 25–30 %) (Zeb and Lodhi, 2025[36]; Benhanifia et al., 2025[37]). Compared to reactive or schedule-based regimes, these systems also lower maintenance costs (Florian, Sgarbossa and Zennaro, 2021[38]) (see Box 2 for examples of AI use in manufacturing). These efficiencies allow firms to expand production without equivalent increases in staff or cost, enhancing competitiveness (Gupta, 2025[21]).

Box 2. Use of AI in the manufacturing sector

- **Predictive maintenance and MRO (maintenance, repair, operations).** Generative AI can help forecast equipment failures by analysing sensor, log and maintenance history data; generate diagnostic suggestions or "next-step" interventions; and optimise spare parts inventory (Santamaria, 2024[39]). In the aerospace sector, airlines and MRO providers are piloting AI "copilot" assistants that technicians can query (e.g. "What might cause a leak in compressor X?"), drawing on maintenance manuals, historical repairs and sensor data. AI tools can also streamline part planning, align procurement with expected failures, and reduce unplanned downtime. (McKinsey & Company, 2024[40]; MarketsAndMarkets, 2025[41])
- **Digital twin and data integration.** Some MRO or manufacturing firms use digital twin models, i.e. virtual replicas of physical machines or systems, that are continuously updated with sensor data. Generative AI may use these digital twins for simulation, anomaly detection, and "what-if" scenarios, enabling more advanced diagnostics or maintenance planning (MarketsAndMarkets, 2025[41]; Apostolidis and Stamoulis, 2021[42]).

- **Quality inspection and defect detection**. In manufacturing lines, AI models (often combining convolutional neural networks, generative adversarial networks or autoencoder architectures) are used to detect microscopic defects, anomalies or deviations beyond human inspection thresholds. Some systems incorporate generative modules to synthesise rare defect variants for training, increase robustness to edge cases (Kumbhar et al., 2023[43]). In trimming-die design, for example, one system automates inspection by integrating AI modules with CAD, reducing inspection time by ~80 % relative to expert manual inspection (Lee et al., 2023[44]).
- **Design automation and generative manufacturing.** More recently, generative manufacturing systems have been proposed whereby AI (e.g. diffusion models, prompt-based systems) can assist in layout design, production sequencing, and component configuration. In one prototype, a generative manufacturing system reduced decision latency and improved responsiveness to changing constraints, allowing more flexible production (Li et al., 2024[16]).

Sources: Apostolidis and Stamoulis (2021[42]), An AI-based Digital Twin Case Study in the MRO Sector, https://doi.org/10.1016/j.trpro.2021.09.007; MarketsAndMarkets (2025[41]) AI Impact Analysis on Digital MRO Industry, https://www.marketsandmarkets.com/ResearchInsight/ai-impact-analysis-on-digital-mro-industry.asp; McKinsey & Company (2024[40]) The generative AI opportunity in airline maintenance, https://www.mckinsey.com/industries/aerospace-and-defense/our-insights/the-generative-ai-opportunity-in-airline-maintenance; Kumbhar et al. (2023[43]) DeepInspect: An AI-Powered Defect Detection for Manufacturing Industries, https://doi.org/10.48550/arXiv.2311.03725; Lee et al. (2023[44]) Automation of Trimming Die Design Inspection by Zigzag Process Between AI and CAD Domains, https://arxiv.org/abs/2305.16866v1; Santamaria (2024[39]) Blog, Industrial Parts, Industrial Technology, https://www.advancedtech.com/blog/ai-and-industrial-mro; Li et al. (2024[16]) Generative manufacturing systems using diffusion models and ChatGPT, https://arxiv.org/abs/2405.00958v2.

27. In high-volume customer support services (in sectors such as large e-commerce platforms, major telecoms, large financial institutions and global SaaS/IT service providers), AI systems may benefit from economies of scale, as per-interaction costs decline with rising volumes, potentially offering efficiency gains compared to human operations which require additional staffing, benefits, facilities and training. Although enterprise-grade deployment can entail significant upfront expenditure, estimates suggest that these may be recovered within a relatively short implementation period, depending on usage intensity.[5] Once in place, AI agents can operate at around USD 0.25–0.50 per interaction – compared with USD 3–6 for human agents and up to USD 15 per interaction for complex tasks, or working overtime – suggesting substantial scope for variable cost reduction (teneo.ai, 2025[32]).

28. AI adoption may also reduce reliance on external business process services (e.g. customer support, data entry, payroll processing, translation, or IT services)[6] and related agency fees, by enabling in-house execution of tasks that were previously outsourced. The best performing organisations report outsourcing cost reductions of USD 2 million-10 million annually and a 30% decrease in the costs of external creative or content generation, including translations, from switching to GenAI for tasks previously outsourced (MIT, 2025[45]; CMA, 2023[46]).[7],[8] In the audit sector, AI adoption has been linked to lower audit fees and reduced staffing needs, attributed to improved accounting quality and reduced information asymmetry. The authors interpret this as AI enabling more efficient audit and accounting processes, displacing routine labour and lowering variable internal costs (Lai, 2025[47]; Fedyk et al., 2022[48]). In knowledge-intensive activities, AI can accelerate design and development cycles and automate administrative functions, helping smaller firms to reduce unit costs and compete more effectively in digitally intensive sectors (Babina et al., 2024[49]; Gupta, 2025[21]).

29. AI capabilities can also be used across different domains, improving the return on upfront investments. For instance, the GenAI used in customer service can also be adapted for compliance monitoring, sales forecasting, or internal documentation. Access to third-party foundation models via APIs or open-source tools allows firms to deploy “plug-and-play” capabilities (e.g. chatbots, image generation, code synthesis) that can be adapted to specific use cases without training their own models (OECD, 2024[2]; Chui et al., 2023[22]). Such modularity may reduce fixed costs, shorten development cycles and

lower the minimum efficient scale required to compete in AI-enabled service markets (Brynjolfsson, Li and Raymond, 2023[15]; OECD, 2024[50]; Gupta, 2025[21]). For instance, a start-up offering financial analysis tools can integrate a third-party generative model to provide natural-language query functionality (chatbots) to clients, without having first to train its own large-scale model (see (Yang et al., 2023[51])).

30. Such efficiencies may lower the cost of innovation and support entry into adjacent or previously unattainable markets, with indications of improved performance outcomes such as reduced defect rates, lower energy consumption and greater supply chain resilience (Calvino, Haerle and Liu, 2025[7]; Calvino, Reijerink and Samek, 2025[5]).

31. Modularity is not unique to AI. Many other, new general-purpose technologies, such as cloud computing, APIs, or Services-as-a-Service (SaaS) platforms have also enabled scalable deployment. Accordingly, the pro-competitive effect of AI may depend on broad, affordable and non-discriminatory access to these tools (OECD, 2025[3]; CMA, 2023[46]; Agrawal, Gans and Goldfarb, 2018[29]). Where such access is open, AI can enhance market contestability by enabling smaller firms to enter and scale in markets that were previously dominated by incumbents with proprietary infrastructure and large datasets. In the financial sector, Fintechs can use third-party AI models to assess creditworthiness using alternative data, bypassing the need for traditional credit scoring infrastructure (CGAP, 2024[52]) (see Box 3.). This may reduce scale advantages and allow firms to compete more on ideas, speed and customer insight rather than size.

Box 3. AI-driven credit scoring can boost alternative finance

In the domain of financial services, AI is being leveraged to expand access to credit for underserved populations across Africa. The Consultative Group to Assist the Poor (CGAP) has highlighted how financial institutions and fintech startups are using AI to analyse alternative data sources – such as mobile phone usage, transaction histories, and social media behaviour – to assess creditworthiness.

This approach is particularly relevant in contexts where formal credit histories are rare or non-existent. By using AI to interpret behavioural and transactional data, lenders can offer microloans and tailored financial products to individuals and small businesses that would otherwise be excluded from formal financial systems. Moreover, AI enables automated customer service and fraud detection, reducing operational costs and improving service delivery.

The competitive impact of these innovations is twofold. First, they enable a broader range of actors to access capital, thereby increasing the number of market participants. Second, they allow smaller financial institutions and fintechs to compete with established banks by offering more agile and inclusive services. This contributes to a more diversified and competitive financial ecosystem.

Source: CGAP (2024[52]) "Data and AI for Inclusive Finance", https://www.cgap.org/topics/collections/data-and-ai-for-inclusive-finance.

Productivity gains

32. Several studies have also tried to measure increases in productivity from using AI tools. Some of the tasks included customer support in the form of resolving queries, (Brynjolfsson, Li and Raymond, 2023[15]); mid-level writing such as press-releases, reports and emails (Noy and Zhang, 2023[17]); economic research (ideation, data analysis and mathematical derivations) (Korinek, 2023[53]); professional services tasks (text and coding, summarising, translating, drafting) (Eloundou et al., 2024[12]) as well as cognitive tasks in writing, coding, planning, translating and summarising for cognitive workers (doctors, lawyers managers, researchers) (Baily, Brynjolfsson and Korinek, 2023[54]). Most of the above studies find positive productivity gains, of between 10%-20%, reaching up to 35% for more low-skilled agents (Brynjolfsson, Li

and Raymond, 2023[15]). Baily, Brynjolfsson and Korinek find a potential increase in the level of GDP of 18% over ten years (Baily, Brynjolfsson and Korinek, 2023[54]). Experimental evidence shows significant productivity gains from using AI chatbots for professional use (see Box 4).

Box 4. Experimental evidence on the productivity effects of generative AI

In a controlled study measuring the productivity effects of generative AI in professional tasks, Noy and Zhang (2023) conducted a randomised controlled trial involving 444 university-educated professionals across various sectors, including marketing, human resources, consulting, and data analysis. Participants were recruited via an online labour platform and asked to complete a series of business-writing assignments simulating real-world professional outputs such as press releases, analytical summaries, and policy briefs.

Participants were randomly assigned to either a treatment group with access to ChatGPT or a control group without access. Each participant completed two writing tasks: one before and one after ChatGPT was introduced to the treatment group, allowing the authors to capture both cross-sectional and within-subject changes in output quality and efficiency. Task quality was evaluated by an independent panel blind to treatment status, based on criteria such as coherence, accuracy, tone, and persuasiveness.

The results show a marked increase in productivity among users of generative AI tools. Access to ChatGPT reduced task completion time by around 40% and increased output quality ratings by approximately 18%, leading to an overall productivity gain of about 37%. The productivity improvements were most pronounced among lower-skilled participants, who closed much of the gap with higher-skilled peers. This suggests that generative AI may act as an "equalising technology" in written communication tasks, potentially levelling skill disparities in cognitive and creative work.

The study also found that workers tended to integrate AI into their workflow strategically, using it to structure drafts, refine tone, and correct grammar, rather than fully delegating the writing task. However, follow-up qualitative analysis indicated that repeated reliance on ChatGPT led to increasing stylistic convergence, with outputs becoming more formulaic and less distinctive over time. The authors warn that this "homogenisation effect" could limit creativity, diversity of thought, and differentiation in markets relying heavily on written content.

Finally, the authors emphasise that may overstate short-run productivity gains and do not capture potential long-term trade-offs such as skill erosion, diminished originality, or shifts in professional norms. The study concludes that while generative AI can substantially enhance individual task performance in the short term, the aggregate and sustained productivity impacts across firms and sectors remain uncertain.

Source: Noy, S. and Zhang, W. (2023[17]) Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence, https://ssrn.com/abstract=4375283.

33. What seems to be common in these studies is that using AI frees staff from routine tasks, enabling them to focus on higher-value activities, which supports in-firm productivity gains. A LinkedIn/Ipsos survey found that 84% of salespeople saved at least 30 minutes per day through AI, and 65% said it helped them exceed quotas. More than 70% of executives expressed confidence in AI managing core functions such as forecasting and account research. Firms also report improved customer outcomes: AI-powered outreach systems have boosted customer retention by 10% in some cases and increased the identification of sales "leads" by up to 40%[9] (LinkedIn/Ipsos, 2025[55]). In some sectors, AI adoption may fundamentally change business models and raise productivity at scale.[10] In agriculture, for example, AI-enabled systems

for crop monitoring and predictive management have been shown to boost output and resilience, offering particular benefits for smallholders facing the challenges of climate change (see Box 5.).

Box 5. Generative AI for agricultural support in Malawi

In Malawi, the deployment of generative AI technologies has begun to transform the agricultural landscape for smallholder farmers, particularly as climate-related disruptions are rising. One initiative involves the use of a locally adapted AI chatbot named Ulangizi, which means “advisor” in Chichewa. Developed by Opportunity International, this tool operates via WhatsApp and is capable of delivering agronomic advice in local languages, including audio responses for users with limited literacy.

The chatbot was introduced in response to the devastation caused by Cyclone Freddy, which displaced thousands of farmers and destroyed crops across southern Malawi. One such farmer, Alex Maere, lost his maize fields and was forced to reconsider his farming strategy as the hurricane altered the soil quality. With guidance from the AI chatbot, Mr Maere planted potatoes in addition to his staples, corn and cassava, ultimately earning over USD 800 from his potato harvest alone. This income enabled him to pay school fees for his children and reinvest in his farm, demonstrating the potential of AI to support rapid recovery and resilience among small-scale producers. The United Nation’s International Fund for Agricultural Development believes that AI has the potential to uplift agriculture in sub-Saharan Africa, where an estimated 33-50 million smallholder farms such as Mr Maere's produce up to 70-80% of the food supply. Private investment in agriculture-related tech in sub-Saharan Africa went from USD 10 million in 2014 to USD 600 million in 2022, according to the World Bank.

From a competition perspective, using such AI-powered advice can reduce barriers to agronomic expertise, which have traditionally favoured larger, better-resourced farms and better educated farmers. By providing tailored, real-time advice to smallholders, AI may enable more equitable participation in agricultural markets and enhances the productivity of previously disadvantaged producers.

Source: Gondwe (2025[56]) “In Malawi, small-scale farmers turn to AI technology for advice”, https://phys.org/news/2025-09-malawi-ai-technology-small-scale.html.

34. These productivity gains may not always materialise. At the economy-wide level, productivity growth may be hindered by the fact that certain tasks cannot be fundamentally altered even with AI, however, wages will still increase, thereby lowering productivity. This is the so-called Baumol effect. Some tasks (for instance, brick-laying) are still executed more or less as they have been for centuries, or a symphonic orchestra will still take the same time to perform Beethoven’s 5th Symphony today as when it was first performed, but the workers or musicians will be receiving today’s wages. Extended across a large number of sectors that benefit less from technology-driven output gains, this Baumol effect will undermine economy-wide productivity gains (Filippucci et al., 2025[14]). This is also related to the fact that some sectors are naturally more prone to AI adoption and exposure than others (see Section 2.3).

35. Some evidence also indicates that AI use may even reduce efficiency in certain contexts. A randomised controlled trial found that experienced developers using early-2025 AI coding assistants completed tasks around 19% more slowly, suggesting that automation may interfere with expert workflows (Becker et al., 2025[57]). AI-assisted code writing has also been associated with additional security vulnerabilities, as some assistants are trained on erroneous public code, potentially generating rework that offset short-term gains (Sandoval et al., 2023[58]). A systematic review of AI in software engineering likewise concluded that, while AI can accelerate development and support proficiency, hidden vulnerabilities in generated code may increase cybersecurity risks and reduce net productivity gains (Negri-Ribalta et al., 2024[59]). Further, several studies suggest that efficiency improvements accrue mainly to lower-skilled workers, implying that for some expert tasks, AI may offer more limited benefits (Baily,

Brynjolfsson and Korinek, 2023[54]). Taken together, these findings point to a more nuanced assessment of AI's impact on performance, where potential time savings may be offset by quality control and security demands.

36. Overall, this aligns with findings that the productivity and innovation effects of AI appear heterogeneous and highly context-dependent, with potential gains sometimes constrained by quality, security and skill-related challenges (Filippucci et al., 2024[60]). While AI adoption can reduce marginal costs and improve scalability, its competitive implications depend on how such efficiencies are distributed across firms. In theory, lower costs should enable more firms to enter and compete. In practice, however, firms with established scale, data assets and cloud infrastructure may be better positioned to benefit, as they can more readily absorb high upfront investment in AI systems. This raises the possibility of asymmetric gains, where incumbents strengthen their position by leveraging AI to reinforce economies of scale and scope, potentially widening an "AI-divide" (Acemoglu, 2024[30]; Korinek, 2024[33]; Kergroach and Héritier, 2025[24]). In other words, AI may support more competition in some markets, but may also entrench market power in others.

2.1.4. Data access and downstream contestability

37. Access to high-quality data plays a central role in shaping both upstream and downstream dynamics in AI markets. At the upstream level, proprietary datasets and cloud infrastructure are widely recognised as essential inputs for training foundation models, in addition to compute and skills (OECD, 2024[2]; European Commission, 2023[61]). These models require vast amounts of high-quality data and significant computational resources, often only available through large-scale cloud platforms (OECD, 2025[3]; 2024[2]; Vipra and Korinek, 2023[62]). There is emerging evidence to suggest that access to these inputs is increasingly concentrated among a small number of firms, including major cloud providers and model developers, the so-called hyperscalers, who control both the infrastructure and the data pipelines necessary for large-scale training (OECD, 2025[3]; FTC, 2023[63]). This has been discussed extensively by other OECD work, but concern is emerging that this concentration may limit the ability of smaller firms or new entrants to develop competitive alternatives, particularly where access to proprietary datasets or compute is restricted or bundled with other services (OECD, 2025[3]; OECD, 2025[4]; OECD, 2024[50]; Villalobos et al., 2024[64]). That said, while access to proprietary datasets may confer advantages, recent analysis suggests that many data sources used for training AI models are non-unique and substitutable, limiting the potential for exclusionary control (Hagiu and Wright, 2025[65]). Moreover, many data licensing agreements are non-exclusive, which may help preserve contestability in downstream markets. The implications of upstream concentration for downstream markets depend on whether access to trained models and enabling infrastructure is broad-based, interoperable, and competitively priced.

38. Downstream, firms deploying AI systems often require access to operational or user-generated data to adapt and fine-tune models bought off-the-shelf to specific tasks, improve performance, and personalise services. In sectors such as finance, health, or retail, where such data are likely to be proprietary, incumbents may benefit from large volumes of interaction data, which can be used to fine-tune models and reinforce service quality (André et al., 2025[66]; Calvino, Reijerink and Samek, 2025[5]). Smaller firms or new entrants may face challenges in accessing comparable data, which can affect their ability to compete on accuracy, efficiency, or customer experience. These dynamics are particularly relevant where AI systems rely on continuous feedback to improve, and where data access determines the scope for innovation and differentiation.

39. The extent to which upstream concentration cascades into downstream markets then depends on several factors, including the availability of interoperable models, the portability of data, and the contractual terms governing access. Open data initiatives and public datasets can help reduce entry barriers, but the availability of such resources is uneven across sectors and jurisdictions. Technical and legal barriers to switching or multi-homing may reinforce dependence on dominant providers, especially where compute

and data services are bundled. Ensuring contestability in downstream markets may therefore require attention to data governance frameworks, interoperability standards, and the practical enforceability of access rights. A different point is the fact that AI might make data accessible and useful, both to those who hold the data, and also to those who might be given access to it. Making information more accessible reduces information asymmetries, which may in turn facilitate a level playing field, and reduce potential barriers to entry.

40. While further analysis is needed to assess the magnitude of these effects, data access likely remains a relevant parameter in evaluating the competitive impact of AI adoption across the value chain (OECD, 2024[2]; CMA, 2024[67]). From a competition perspective, relevant parameters to observe are likely to include the availability of interoperable data sources, the terms of access to proprietary datasets, the enforceability of portability rights, and the extent to which data access enables meaningful adaptation or differentiation of AI applications. Monitoring these factors may help assess whether upstream concentration risks translate into reduced contestability in downstream markets (OECD, 2024[2]; CMA, 2024[67]; Gupta, 2025[21]).

2.1.5. Model access and downstream differentiation

41. While foundation model development requires substantial data and compute resources, most downstream firms do not build their own models. Instead, they rely on access provided by a small number of upstream providers through APIs, plug-ins, or hosted platforms. The degree to which these models can be adapted or fine-tuned – sometimes referred to as “model openness” – influences how firms can integrate AI into their operations. However, it is not openness alone that matters for competition, but rather the practical ability of firms to access and tailor models to their specific needs. “API-gated” systems, i.e. closed models that interact through API endpoints, may offer convenience and reliability, but they can also limit visibility, control, and scope for differentiation. Conversely, semi-open or open-weight models may allow firms to fine-tune systems using proprietary data, enabling more targeted and differentiated applications and potentially supporting innovation in niche or sector-specific contexts (OECD, 2025[68]; Calvino, Haerle and Liu, 2025[7]; CMA, 2024[67]). The diversity of downstream use cases and modalities at present suggests that foundation models are unlikely to exhibit winner-takes-all dynamics across all sectors (Hagiu and Wright, 2025[65]).

42. From a competition perspective, the relevant parameters would include the extent to which downstream firms can customise models, the availability of interoperable alternatives, and the contractual or technical constraints on switching. The Portuguese Competition Authority has stressed that model openness is a critical determinant of contestability (AdC, 2024[11]). Where models remain closed and accessible only via APIs, downstream firms are likely to face dependence on provider terms (AdC, 2024[11]). This could potentially raise risks of refusal to supply, tying, self-preferencing or exploitative pricing, similar in effect as what has been observed in jurisprudence under Article 102 TFEU in Europe (European Commission, 2018[69]). Such risks could arise in cloud marketplaces (Model-as-a-Service), where hyperscalers act as both suppliers and gatekeepers (OECD, 2025[3]). The French *Autorité de la concurrence* notably has emphasised these risks, identifying cloud lock-in, exclusive data partnerships, and vertical integration as potential foreclosure channels in its Opinion (Autorité de la concurrence, 2024[70]).

43. While widespread access to general-purpose tools may compress productivity gaps, it may also standardise business processes and limit differentiation. Therefore, the ability to fine-tune models using firm-specific data could become a source of competitive advantage, particularly in sectors where domain knowledge or regulatory adaptation is important. However, such strategies often require complementary assets – such as compute, talent, and integration capacity – which may not be evenly distributed across firms. As such, competition authorities may wish to monitor whether access conditions, licensing terms, or

ecosystem dependencies restrict downstream contestability, especially where switching costs or interoperability limitations arise (Krakowski, Luger and Raisch, 2022[26]; OECD, 2025[68]; Gupta, 2025[21]).

44. For SMEs and firms in less represented sectors or regions, downstream AI tools such as plug-ins, APIs, and pre-trained applications can lower barriers to adopting digital technologies and improve efficiency (OECD, 2025[68]; Calvino, Reijerink and Samek, 2025[5]). However, as will be discussed in section 2.3., uptake remains uneven as while SMEs often lack the technical skills, infrastructure, or complementary assets to integrate and use these tools effectively, risking a widening AI capability divide (OECD, 2024[50]; Kergroach and Héritier, 2025[24]).

2.1.6. Search and switching costs

45. A final way that AI can support competition in downstream markets is by lowering lower consumers' search and verification costs. AI-enabled search, recommender and conversational systems filter, rank and personalise consumer options, which increases matching efficiency and the incidence of comparison across offers. This mechanism broadens effective choice sets and can foster or intensify competitive pressure on price and quality. Reviews of algorithmic recommendations explicitly note that such systems "save time and search costs", while also cautioning about design choices that might counteract these gains (Calvano et al., 2024[71]). Building on formal consumer-search models, recent theory shows that personalisation creates value precisely by reducing search costs, drawing out higher-value (previously inactive) consumers and changing search breadth at the intensive margin (Rafieian and Yoganarasimhan, 2023[25]). Empirical work on AI-assisted information search similarly highlights that AI tools can reduce the time and effort required to locate and assess alternatives, facilitating more efficient consumer decision-making (Pham, Pham Thi and Duong, 2024[72]).

46. However, from a competition perspective, these systems may also create new frictions: by shaping consumer exposure through ranking or recommendation biases, they can channel demand towards certain suppliers, reducing effective transparency and potentially reinforcing incumbency advantages. The opacity of recommender algorithms further limits contestability if rival firms cannot ensure visibility under fair conditions, while consumers' reliance on AI intermediaries may heighten switching costs or enable discriminatory steering based on inferred willingness to pay (Calvano et al., 2024[71]).

2.2. Limits to the usefulness of AI systems

47. While most of the findings discussed above point to a degree of cost reductions and productivity gains from adopting AI, with noted caveats, there are other, less positive, effects of the use of AI systems.

48. Several studies indicate that AI adoption may affect the quality and diversity of creative and cognitive work. Experimental evidence shows that the use of LLMs tends to homogenise creative outputs, reducing idea diversity and originality (Anderson, Shah and Kreminski, 2024[73]). In the context of marketing, AI-generated content has been found to be more repetitive and less engaging for consumers. Specifically, content generated by popular LLMs may appear more similar to each other compared to human created content, known as *content homogenisation*. This suggests diminishing returns on creative differentiation from using LLMs without human input (Liu, Wang and Yang, 2025[74]).

49. In scientific communication, LLMs have been shown to oversimplify and misrepresent research abstracts, thereby compromising accuracy and interpretative depth. This is especially problematic for scientific studies, since scientists must frequently include qualifications, context and limitations in their research results. Scientists discovered that some versions of popular chatbots were five times more likely to oversimplify scientific findings than human experts in an analysis of 4 900 summaries of research papers (Peters and Chin-Yee, 2025[75]). Moreover, AI-powered chatbots, including LLMs, are prone to generating inaccurate or fabricated information – a phenomenon commonly referred to as "hallucination". These errors

can arise even when the model appears confident and fluent, undermining its reliability in high-stakes or information-sensitive contexts. While ongoing research aims to reduce such occurrences, the persistence of hallucinations poses challenges for trust, accountability, and safe deployment in both public and private sector applications (OECD.AI, 2023[76]).

50. Cognitive research further shows that reliance on AI tools can weaken users' analytical and critical-thinking capacities over time: a recent study revealed a significant negative correlation between frequent AI tool usage and critical thinking abilities, owing to increased cognitive offloading (i.e. outsourcing parts of one's thinking or memorising). Younger participants exhibited higher dependence on AI tools and lower critical thinking scores compared to older participants (Gerlich, 2025[77]). While deep integration with AI (i.e. actively interacting with the AI to generate content) has been found to foster new skill acquisition, passive use, such as delegating and automating tasks, might erode knowledge. Similar studies have found that delegating writing tasks fully to an AI system can reduce neural, linguistic and behavioural performance (MIT Media Lab, 2025[78]). Indeed, an overreliance on AI could erode human knowledge over time (Baily, Brynjolfsson and Korinek, 2023[54]). On the other hand, productivity gains are maximised when AI is deployed to well-defined and bounded tasks, such as coding, writing and summarising, and integrating AI as a complement rather than a replacement for human skills (Calvino, Reijerink and Samek, 2025[5]).

51. The next section takes a brief look at the way sectors and tasks are exposed to AI, with potential ramifications for AI-use.

2.3. Sector exposure and uptake of AI vary significantly

52. To help identifying sectors that are more likely to see the largest impact from AI adoption, this section looks at potential sector exposure to AI based on types of occupation, followed by a discussion on observed AI uptake.

2.3.1. Sector exposure to AI is high for professional services

53. As discussed above, exposure to AI automation or substitution varies significantly across sectors, one of the reasons for the Baumol effect mentioned earlier. A large study by (Eloundou et al.[12]) investigates the potential labour market impact of GenAI, by assessing how exposed various occupations and tasks are to LLM capabilities.[11] The authors identify ***exposure*** as the extent to which LLMs can reduce the time required to complete a task by at least 50% without compromising quality; and ***automation*** as the extent to which LLMs (and LLM-powered software) can fully or mostly perform a task without human oversight. This is relevant as a potential gauge of where AI-adoption may lead to disruption or structural changes that affect the competitiveness of market players.

54. The Eloundou study finds that a large share of United States workers (80%) are in occupations with at least 10% of tasks exposed to LLMs, and 18.5% of workers are in occupations where over 50% of their tasks are exposed to LLMs. The most exposed occupations include professional and business services, including mathematicians, writers and authors, tax preparers and auditors, financial quantitative analysts, web and digital interface designers and coders, whereas exposure is lowest in manual occupations, including cement masons, roofers, meat packers, bus mechanics and dishwashers.[12]

55. Concurrent with the findings in Section 2.2, the tasks with high exposure also correspond to those listed above where the use of GenAI tends to compress the duration for routine tasks, reduce the need for some types of labour and lead to cost reductions or higher productivity, potentially therefore lowering barriers to entry. Such effects are already visible in areas like software development, legal and accounting services (professional services), and in customer service and business process outsourcing, including supply-chain management (Peng et al., 2023[18]; Cui et al., 2024[19]; McKinsey, 2025[79]; André et al.,

2025[66]; Calvino, Reijerink and Samek, 2025[5]; Brynjolfsson, Li and Raymond, 2023[15]; Rajendran, Balaraman and Viswanathan, 2025[80]). [13]

56. Sectors relying on physical or on-site tasks, such as maintenance or logistics operations, remain less affected by AI. While predictive-maintenance systems in manufacturing use AI to forecast failures and optimise parts procurement, the machines still depend on human technicians for diagnosis and repair (Santamaria, 2024[39]; McKinsey & Company, 2024[40]). In logistics and retail, AI modules can assist small firms in demand forecasting, stock management and routing, significantly increasing throughput and effectiveness and boost competitiveness, even though staff are still required for handling and delivery functions (Dicey, 2025[81]; Nishar, 2024[82]; Shen et al., 2025[83]).[14]

57. Differences in task exposure may shape the potential for GenAI to alter market structures and support competitive outcomes. As such one may argue that sectoral exposure to GenAI is a key determinant of the likely competitive impact from AI adoption. In sectors where a large share of tasks can be automated or augmented, competing firms may in principle replicate the capabilities of incumbents by adopting generative-AI tools, provided that access costs for data, models and computing resources remain manageable (Kergroach and Héritier, 2025[24]). The ability to translate automation potential into genuine contestability however also depends on whether new entrants can overcome other structural barriers such as brand recognition, distribution channels, or regulatory complexity.

58. Hence, AI’s potential to reshape competition is contingent on both technological exposure and institutional context. The creative industries illustrate this tension: although writing, editing, design and composition tasks are among the most exposed to GenAI, incumbents can retain advantages through control of intellectual-property assets and established reputations, while legal uncertainty surrounding copyright and text-and-data-mining frameworks might discourage entry by smaller creators (Lucchi, 2025[84]; Marcelin and Cassetti, 2025[85]).

2.3.2. AI uptake is rising

59. This section reviews some of the available evidence on the uptake of AI. As the use of AI (and the technology itself) are constantly evolving, the data are illustrative rather than authoritative.

60. Confirming the discussion above, knowledge-intensive services are consistently among the most advanced AI users: in 2024, 44% of firms in the information and communication sector in the OECD area reported using AI, with figures above 67% in Denmark, Sweden and Finland (Kergroach and Héritier, 2025[24]). Professional, ICT, finance and scientific services showed an average of 26% adoption across the OECD, while utilities reported similar levels, with much higher figures in northern Europe. Other sectors that have seen a widespread uptake of AI are sales, marketing and customer-facing functions (MIT, 2025[45]). By contrast, adoption remains low in food products, textiles, construction and hospitality (Kergroach and Héritier, 2025[24]; OECD/BCG/INSEAD, 2025[27]).[15]

61. Firm size remains one of the strongest predictors of AI use. In 2024, 39% of large firms in the OECD area reported using AI, compared with 12% of small firms; a 3.3-fold difference (Kergroach and Héritier, 2025[24]). Larger firms are also more likely to report redesigning workflows and embedding AI into multiple business functions, from IT and marketing to service operations (McKinsey, 2025[79]).

62. Adoption is often limited by a lack of digital and data maturity, and uncertainty about return on investment (OECD/BCG/INSEAD, 2025[27]). Skills shortages are cited for high-tech industries such as computer and electronics manufacturing, utilities, telecommunications and travel agencies. Lack of expertise, incompatibility or lock-in with existing legacy systems, and high costs are also cited as reasons for not adopting AI. Legal uncertainty is also increasing, with more firms reporting difficulties understanding AI-related obligations. MIT reports that over 80% of organisations have piloted general-purpose tools, but only 20% reached pilot stage, and just 5% of AI systems that are trialled and fully deployed. This gap has been described by MIT as the “GenAI Divide”, reflecting widespread experimentation but limited

transformation within firms (MIT, 2025[45]). Difficulties in accessing quality data and compliance with privacy rules are also frequently cited (Kergroach and Héritier, 2025[24]).[16] AI-related risks related to cybersecurity, intellectual property and data governance are also holding back uptake, even in AI-advanced sectors like professional services and publishing (Kergroach and Héritier, 2025[24]; McKinsey, 2025[79]).

63. AI-use may however be starting to alter the market structure in selected industries, with potential competitive ramifications. MIT (2025[45]) found that two of nine surveyed sectors (technology and media) have experienced structural change attributable to GenAI, such as shifts in recruitment, business models or market leadership. In other industries however, adoption remains incremental, focused on efficiency gains rather than disruption. Nonetheless, surveys suggest that early adopting firms that invest in customised, workflow-integrated AI systems are gaining a competitive advantage. These include revenue growth of 3%–15% and shorter times to market (OECD/BCG/INSEAD, 2025[27]; MarketsAndMarkets, 2025[41]). Furthermore, a survey carried out by LinkedIn/Ipsos amongst sales forces shows that 73% of sellers believe they will be left behind without an AI strategy, and 75% of top-performing sellers are eager to adopt AI agents (LinkedIn/Ipsos, 2025[55]).

64. Finally, new forms of so-called "shadow AI" use are emerging: While only 40% of companies report purchasing official LLM subscriptions, employees in more than 90% of surveyed firms report regular use of personal AI tools for work tasks (MIT, 2025[45]). This informal uptake suggests that adoption is often moving faster at the individual than at the organisational level, and may in time accelerate enterprise deployment. India seems to be following these trends (Box 6).

Box 6. AI uptake and diffusion in downstream sectors in India

India's AI market has nearly doubled in value since 2020, growing from USD 3.2 billion (2020) to USD 6.1 billion in 2024. AI adoption has seen a rapid expansion across downstream sectors, driven by government initiatives, startup activity, and increasing private sector investment. The *IndiaAI Mission*, launched in 2024 with funding of around INR10 300 crore (USD 1.2 billion), aims to expand national compute capacity, create a shared dataset platform and promote indigenous AI models. These measures aim to reduce reliance on a few global providers and make advanced AI infrastructure accessible to smaller firms.

Adoption has been fastest in IT and digital services, financial technology, manufacturing and agriculture. Large Indian firms are scaling from pilot projects to production-level AI use in process automation, analytics and customer engagement, while public-private initiatives in agriculture are using AI to forecast weather, soil and pest conditions through mobile-based advisory systems. The Competition Commission of India (CCI), in its market study on AI and Competition (September 2025), notes that Startups dominate the downstream layers, especially in application development, with 67% of surveyed firms focused on building AI-powered solutions. They are helping democratise AI adoption across sectors while navigating challenges like infrastructure costs, data access, and ecosystem lock-in.

AI appears to be already producing pro-competitive effects in selected niches. By enabling lower-cost predictive analytics, demand forecasting or customer personalisation, AI tools allow smaller firms to enhance operational efficiency and differentiate their offerings. The *IndiaAI Mission*'s stated objective is precisely to "democratise computing access" and support indigenous innovation, thereby enabling smaller players to participate more fully in the AI ecosystem. Open or shared compute infrastructure and dataset platforms can serve as common inputs, helping to level the playing field if governed on fair, transparent and non-discriminatory terms.

However, AI-diffusion remains uneven. Most adoption is concentrated among large firms in major cities, while smaller enterprises face barriers related to skills, infrastructure and data access. These gaps risk widening productivity and competitiveness divides. At the same time, concentration in compute resources, cloud services and foundational models may allow a few firms to shape downstream access, creating dependencies and potential foreclosure risks. The CCI has highlighted issues such as preferential access to AI inputs, bundling and tying, as areas requiring close monitoring.

The CCI market study notes that competition risks in the AI ecosystem are multifaceted and evolving. It further highlights concerns about market concentration, particularly the dominance of large technology firms across multiple layers of the AI stack, data, infrastructure, and foundational models, which can create high entry barriers for startups. The market study identifies risks such as algorithmic collusion, price discrimination, self-preferencing, and opaque decision-making, which may distort market outcomes and reduce consumer choice. It also warns of ecosystem lock-in, where users become dependent on specific platforms due to high switching costs. These dynamics, if unchecked, could entrench incumbents, stifle innovation, and undermine fair competition.

Sources: Press Information Bureau (2024), IndiaAI Mission approved by Cabinet, https://www.pib.gov.in/PressReleasePage.aspx?PRID=2178092; IndiaAI, About the Mission, https://indiaai.gov.in/; ISAS (2025), AI Adoption in India: Moving the Needle Forward, https://www.isas.nus.edu.sg/papers/ai-adoption-in-india-moving-the-needle-forward/; Competition Commission of India (2025), Market Study on Artificial Intelligence and Competition, https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf

2.4. The emerging case of Agentic AI

65. Agentic AI is an emerging case, referring to a developing generation of systems that integrate memory, planning, and tool-use to pursue goals with a high degree of autonomy. Unlike traditional LLMs that merely respond to prompts or generate content, agentic systems can initiate actions, interact with external systems, and adapt their behaviour over time, potentially operating independently in real-world or digital environments. These applications act as agents for users, powered by foundation models (FMs), but with substantial decision-making autonomy. Though still nascent, agentic AI could significantly reshape competition in areas such as search, professional services, workflow automation, and assistant tasks (e.g. travel booking, agenda management, procurement, or sales). Agentic AI differs from traditional AI tools because it combines reasoning, planning, memory, and the ability to act autonomously across digital environments, often through multi-agent frameworks (Derouiche, Brami and Mazeni, 2025[86]; Nisa et al., 2025[87]). The OECD has highlighted the importance of monitoring these frameworks closely, given their potential to reshape market structures and regulatory frameworks (OECD, 2024[50]).

66. These advances could mark the beginning of a broader shift towards the “Agentic Web”, characterised by autonomous, goal-driven interactions where AI agents interact directly with one another to plan, co-ordinate, and execute complex tasks on behalf of users (Yang et al., 2025[88]). For instance, instead of generating text or images for a social media post, an AI Agent would post the content directly across a host of social media outlets (Desai and Riedl, 2025[89]). This transition from human-driven to machine-to-machine interaction would eventually allow users to delegate routine digital operations entirely to AI systems, potentially transforming online services and business models.

67. Although still in their infancy, Agentic systems may also be able to further reduce consumer search and transaction costs, discussed in 2.1.6. By aggregating information across multiple providers, these systems could potentially support multi-homing and switching, supporting competition by weakening incumbents’ ability to exploit behavioural biases and consumer inertia (OECD, 2023[90]). Agentic AI may enhance contestability by enabling smaller firms to deploy AI “agents” to co-ordinate workflows, search for information, and interact with customers without requiring extensive technical resources or in-house expertise (Yang et al., 2025[88]; Sapkota, Roumeliotis and Karkee, 2025[91]). Such usage could allow new firms to scale faster and challenge incumbents in areas such as professional services, digital commerce, and back-office operations. However, many agentic AI systems developers rely on cloud integration with

the world's three hyperscalers (OECD, 2025[3]), implying a vertical link for downstream users, which could potentially hamper competition over time.

2.5. Conclusion

68. While comprehensive data on indicators such as entry and exit or firm churn remains limited, the evidence reviewed in this chapter suggests that AI adoption in downstream sectors may support competition. In particular, AI can reduce average and fixed costs, substitute for labour in routine tasks, increase efficiency, and enable new forms of innovation. Firms may benefit where automation frees employees to focus on higher-value activities and reduces reliance on outsourced services.

69. However, these effects are not automatic and may vary substantially across sectors, firm sizes, and use cases. Smaller firms could gain from modular AI tools and task-level automation, but larger incumbents often benefit from structural advantages – such as greater access to data, infrastructure, and integration capacity – which may allow them to capture disproportionate gains. The competitive impact of AI therefore depends not only on technological capabilities but also on market conditions, regulatory frameworks, and access to enabling inputs. Competition conditions upstream, including in markets for compute, model design, and especially data access (CMA, 2023[92]; Autorité de la concurrence, 2024[70]; OECD, 2025[3]; ACCC, 2025[93]) also influence competition downstream.

3 AI-related competition concerns in downstream markets

70. AI can potentially alter the basic dynamics of competition by increasing market transparency and accelerating competitors' reaction times, with possible implications for collusion, exclusionary conduct, and ultimately for consumer welfare as firms can react faster and with more accuracy than in the past (OECD, 2023[90]; OECD, 2021[94]; Hagiu and Wright, 2025[65]). Many of these competition concerns will be "traditional", where familiar theories of harm apply in new technological settings, but there will also be "emerging" concerns specific to how AI systems operate. The following sections will first address traditional enforcement issues that may arise when competitors use AI, before turning to AI-specific challenges such as attribution of liability.

71. As the deployment of AI systems is still comparatively new, their effects on competitive dynamics and potential anti-competitive behaviour are still emerging, with very few actual antitrust cases known at the time of writing. Hence this chapter is intended to provide an outline of likely competition concerns that NCAs may face, rather than an authoritative discussion of observed anti-competitive conduct.

72. While algorithmic conduct is not new in competition enforcement – particularly in relation to pricing algorithms, collusion risks, and hub-and-spoke arrangements – GenAI introduces new dimensions that may warrant distinct consideration. Traditional algorithms typically execute predefined rules or optimise within narrow parameters, whereas generative AI systems are capable of producing novel outputs, adapting to user inputs, and learning from feedback and user prompts in ways that may be less predictable and harder to audit (Mayer Brown, 2024[95]; OECD, 2023[90]; FTC, 2023[63]; Carugati, 2024[96]). This capacity for autonomous content generation and strategic adaptation may complicate the assessment of intent, attribution, transparency and predictability in enforcement settings. For example, while algorithmic collusion may involve observable pricing patterns or shared data inputs, GenAI conduct may manifest through dynamic content generation, evolving recommendation systems, personalised offers or autonomous decision-making that changes over time and influences market behaviour in less transparent ways.

73. The potential for firm- or sector-specific fine-tuning also introduces heterogeneity in how GenAI is deployed, which may affect market outcomes and complicate the assessment of competitive harm (Chapter 2). Firms can fine-tune models to proprietary data or sector-specific needs, potentially enhancing differentiation but also raising questions about access, interoperability, and control (Bostoen, 2025[97]; Bostoen and van der Veer, 2024[98]). Accordingly, some of the parameters of interest may be the degree of model customisation, the governance of model outputs, and the extent to which generative systems are accessed or rather embedded. The factors influence firms' strategic behaviour and may also alter the dynamics of interactions in ways that differ from more traditional algorithmic systems (Hofmann and Lorenzoni, 2023[99]; Alvarez and Marsal, 2025[100]; CMA, 2024[67]).

3.1. Competition enforcement concerns

74. Competition concerns in AI-enhanced downstream markets include risks of horizontal co-ordination as well as unilateral conduct: issues that are typically addressed under existing competition law

frameworks in most jurisdictions. While AI technologies may alter the mechanisms through which such conduct manifests, many of the underlying concerns are familiar from traditional market as well as, more recently, from digital markets. Some of these issues have been the subject of extensive analysis by NCAs and by the OECD Competition Committee. For instance, algorithmic pricing tools have raised new questions about collusion, including hub-and-spoke arrangements and tacit co-ordination, but these are often extensions of known theories of harm such as price-fixing and information exchange (OECD, 2017[101]; 2021[102]; 2021[94]; 2023[90]; 2025[103]). This section will briefly summarise some of the more familiar or potentially expected competition concerns that NCAs may encounter in downstream AI markets.

3.1.1. Horizontal co-ordination and algorithmic collusion

75. AI systems increase both transparency and speed, with ambiguous effects. On the one hand, the ability of AI to provide rapid access to competitor data can increase efficiency. On the other, AI can artificially increase market transparency; if combined with ability of algorithms to react instantaneously to competitors deviations, the use of AI can eliminate incentives to deviate from explicit or tacit arrangements and stabilise co-ordination (OECD, 2023[90]; OECD, 2025[103]). Algorithmic pricing tools, including those powered by GenAI, may, under certain conditions, facilitate co-ordination even without explicit communication between competitors (Autorité de la concurrence and Bundeskartellamt, 2019[104]; JFTC, 2025[105]; OECD, 2025[103]). Rather than businesspeople meeting in a smoke-filled room or on the golf course, now AI-powered algorithms are capable of aligning expectations and responses, to stabilise prices or market shares and reduce incentives or opportunities to deviate: enhanced observability and predictability of rivals' behaviour can soften competition and sustain supra-competitive outcomes. By continuously monitoring market data, algorithms may align prices or outputs across firms, stabilising oligopolistic equilibria and reducing incentives to deviate (OECD, 2025[103]; OECD, 2023[90]). The 2025 OECD report on algorithmic pricing in G7 jurisdictions distinguishes three settings – algorithm-facilitated explicit collusion, hub-and-spoke co-ordination, and autonomous algorithmic collusion – each with different implications for intent and liability.

Explicit collusion and hub-and-spoke

76. Explicit collusion facilitated by algorithms is where firms use AI systems or algorithmic tools to co-ordinate prices, market shares or other strategic variables in a manner that would traditionally be considered a cartel. While the underlying conduct remains subject to established legal standards, the use of algorithmic tools may alter how collusion is implemented or detected. For example, firms may use shared pricing algorithms, common optimisation software, or third-party platforms to align behaviour without direct communication (OECD, 2025[103]). Although the legal framework for assessing explicit collusion remains largely unchanged, enforcement agencies may face challenges in identifying the locus of decision-making, especially where algorithmic tools are outsourced or embedded in broader service contracts. As such, competition authorities may need to scrutinise the role of intermediaries, the transparency of algorithmic logic, and the contractual relationships between firms and technology providers (OECD, 2025[103]).

77. The risks of algorithmic collusion are expected to be greater where firms use the same pricing software or rely on a common model provider (hub-and-spoke arrangements). The OECD (2025[103]) identifies several enforcement examples, including the by now well-known online posters cases (CMA's Trod/GBE 2016)17 and the United States' Amazon Marketplace posters (U.S. DoJ, 2015[106])), where competitors employed identical repricing software and pricing algorithms to maintain agreed margins on online marketplaces. In such settings, the algorithm serves as an instrument executing a cartel.

78. Hub-and-spoke co-ordination, where a common vendor or platform facilitates collusion on behalf of multiple rivals, can likewise establish a concerted practice if competitors are – or should be – aware that shared algorithms align their behaviour. The EC's Guidelines on the applicability of Article 101 TFEU to horizontal co-operation agreements state that when competitors subscribe to the same third-party pricing

tool, and the tool uses commercially sensitive information from competitors, this may result in an unlawful information exchange (European Union, 2023[107]). The JFTC identified similar distinctions and enforcement implications under the Japanese Antimonopoly Act. If firms using the same algorithm share a common understanding that it will co-ordinate prices – despite no direct communication between the competitors – this may constitute a violation of Japan's Antimonopoly Act (JFTC, 2021[108]).

Tacit algorithmic co-ordination

79. AI pricing tools can reproduce traditional co-ordination in digital form. Even without explicit agreement, it is – so far hypothetically – possible that GenAI with self-learning or reactive algorithms may stabilise prices in oligopolistic markets. By continuously observing market data, algorithms can infer rivals' reactions and converge towards joint profit-maximising equilibria. However, some jurisdictions recognise that mere parallel behaviour without any kind of agreement or contact between competing companies may not constitute an infringement of antitrust laws (OECD, 2025[103]). In the EU, for instance, the EU Court has established that an agreement prohibited under Article 101 TFEU requires some form of communication and sense of mutual commitment ("a meeting of minds" or a "concurrence of wills")[18]. Companies have the right to adapt themselves to the existing or anticipated conduct of their competitors, as long as they determine their policies independently. However, the question here is rather whether the firms' AIs, acting independently with an objective of maximising profits, may lead to a co-ordinated outcome. In this case the analytical challenge is evidentiary – identifying intent and foreseeability.

3.1.2. Unilateral conduct

80. AI can magnify unilateral conduct by dominant firms, including exclusionary and exploitative behaviour. The theories of harm will still correspond to "classic" abuses of dominance: exclusion of rivals or exploitation of consumers and downstream markets through unfair prices, terms or discrimination. Here, it is the relationship with upstream FMs via APIs or plug-ins, that may facilitate the unilateral conduct.

Exclusionary conduct

81. Digital platforms act as curators of online options, with algorithms that determine the visibility of content and products. Because consumers tend to rely heavily on these rankings, platforms acquire significant influence over consumer choice. This power can be abused when the platform is both an intermediary and a competitor: ranking algorithms may systematically favour the platform's own products or services, thereby excluding rivals (Bostoen, 2025[97]). Skewed rankings distort competition by marginalising competitors and misleading consumers, particularly where promoted results are not the most qualitative. AI-driven marketplaces using extensive platform data may be even better at tailoring these ranking to favour their own brands. Similar concerns have been raised over Amazon's Buy Box and algorithmic control of third-party seller visibility. [19]

82. Dominant digital platforms may design AI systems – search, recommendation, or generative interfaces – to favour their own products or affiliated services, acting as "choice architects", guiding firm and consumer behaviour. If such agents systematically favour in-house products, rivals may be excluded despite superior offerings, distorting downstream competition and consumer choice (Autorité de la concurrence, 2024[70]; CMA, 2024[67]; JFTC, 2025[105]). Some authors find that such optimisation can emerge endogenously when algorithms maximise engagement or conversion metrics, even absent explicit exclusionary intent (Hagiu and Wright, 2025[65]; Rafieian and Yoganarasimhan, 2023[25]). Where rivals' visibility is reduced through algorithmic optimisation rather than explicit code, competition authorities face new evidentiary challenges in establishing intent and causality (Bostoen, 2025[97]). The legal assessment would have to be effects-based: if the self-learning system's operation results in the systematic foreclosure of competing products or services, and cannot be objectively justified by relevance or quality criteria, it may constitute an abuse of dominance (Autorité de la concurrence, 2024[70]; Bostoen, 2025[97]; OECD, 2025[103]).

Dynamic and personalised pricing

83. The adoption of AI significantly expands firms' ability to implement high-frequency dynamic pricing and personalised offers, including in sectors where such practices were previously impractical. By processing behavioural and transactional data at scale, AI can estimate willingness-to-pay with precision, enabling granular price discrimination across consumers (OECD, 2024[50]; Tucker, 2024[109]). While such practices can in theory increase efficiency, in practice they often reduce consumer welfare, and may foreclose rivals lacking equivalent data capacity (see for instance, (Ezrachi and Stucke, 2016[110]; OECD, 2021[94]; Tucker, 2024[109]).

84. Reinforcement-learning algorithms can continuously test consumers' willingness to pay, capturing surplus or targeting discounts to deter rivals (OECD, 2025[103]). AI-enabled personalisation and dynamic pricing strategies may facilitate exploitative or exclusionary conduct, particularly when deployed by dominant firms with access to granular consumer data to raise firms' predictive accuracy. By enabling firms to predict consumer preferences with precision, AI can transform pricing into a strategic tool for differentiation and ultimately rent extraction. In this sense, AI shifts pricing from a traditional efficiency mechanism into a strategic moat, enabling more sophisticated discriminatory practices that competitors without equivalent data cannot replicate (Stucke and Ezrachi, 2024[111]).

85. In downstream markets, this could manifest in airlines, insurance, or online retail, where AI systems infer consumers' willingness to pay and set prices accordingly. For instance, while searching for a flight, prices across websites start adjusting. Such services are likely to increasingly rely on Agentic AI, potentially further eroding consumer surpluses. Shared models and datasets may further drive convergence in pricing and business strategies (JFTC, 2025[105]). However, competition law does not always treat price discrimination of final consumers as a relevant conduct.

86. Overall welfare effects may depend on market power and transparency (Rafieian and Yoganarasimhan, 2023[25]). The CMA warns that firms may use AI systems to personalise offers to customers, which could be used strategically to exclude competitors. For example, incumbents might target customers most likely to switch to a rival, making it harder for new entrants to gain traction, especially in concentrated markets, helping reinforce market power. The CMA also highlights that AI-enabled personalisation, including pricing, can be harmful if it unfairly targets vulnerable consumers or has unfair distributive effects. It notes that such practices are difficult to detect and may undermine consumer trust and choice (CMA, 2024[67]).

Predatory pricing through AI-driven systems

87. AI-enabled pricing systems may allow firms to adjust prices with greater speed and granularity, including across products, regions or consumer segments. In theory, machine-learning models could be used to identify competitive threats and respond with targeted price reductions, potentially below cost. In algorithmically driven markets – such as online retail, advertising or ride-hailing – automated price-matching may compress reaction times and reduce incentives to undercut, potentially stabilising prices. Some studies also suggest that shared models or data sources could lead to similar pricing strategies across firms, though further analysis is needed to assess the competitive implications (JFTC, 2025[105]).

88. Such AI-based pricing systems can sustain below-cost pricing for longer periods than human-driven strategies, thanks to algorithmic optimisation and access to granular demand data. This raises concerns that AI-based predation could become both more effective and less detectable, as prices adapt instantaneously to rivals' reactions (Harrington, 2018[112]; OECD, 2023[90]; 2025[103]). Predatory pricing is traditionally difficult to prove. The use of automated systems risks further complicate this. AI can better maintain precision targeting of the below-cost price that would limit losses during the predation phase and accelerate recoupment once rivals exit, potentially even making predation a rational strategy (Rafieian and

Yoganarasimhan, 2023[25]). The Competition Commission of India also warns of the risk of algorithmic unilateral conduct that could resemble predatory pricing (CCI, 2025[113]).

Foreclosure and leveraging

89. Vertical integration between layers of the AI value chain or also within the AI "stack", such as compute infrastructure, model development, and downstream deployment, can generate substantial efficiencies. Integration may lower transaction and co-ordination costs, improve interoperability and technical performance, and strengthen incentives to invest in safety, innovation, and quality across complementary layers (Hagiu and Wright, 2025[65]; CMA, 2024[67]).

90. Vertical integration in AI markets may also enable firms to leverage market power across layers of the AI stack, with significant implications for downstream competition. Control over essential inputs – such as compute, proprietary data, and model interfaces such as APIs – can be used to privilege affiliated services, restrict interoperability, or impose discriminatory conditions (ACCC, 2025[93]; Autorité de la concurrence, 2024[70]; CMA, 2024[67]). These risks are amplified when downstream firms depend structurally on integrated providers for access to models, cloud infrastructure, or APIs, creating lock-in and raising switching costs, especially when AI copilots are bundled with cloud services and productivity software in downstream firms (OECD, 2021[102]; 2025[3]; Vipra and Korinek, 2023[62]; Vipra and Korinek, 2023[62]; Autorité de la concurrence and Bundeskartellamt, 2019[104]).

91. Among these inputs, data access, discussed in Chapter 2, may be a critical bottleneck affecting downstream firms' ability to compete and innovate if there is vertical integration.[20] Proprietary datasets are likely to confer durable advantages to their owners, and without portability or interoperability, there is a risk that this could prevent challengers from entering or scaling in some downstream markets (OECD, 2025[68]; Autorité de la concurrence, 2024[70]). Platforms' control over behavioural signals may also be leveraged, also through tying and bundling practices, into adjacent markets such as advertising, search, and content, reinforcing incumbency (ACCC, 2025[93]).[21] These dynamics reflect a broader theory of harm, i.e. input foreclosure, where a vertically integrated firm restricts rivals' access to essential inputs – whether data, compute, or model interfaces – undermining their ability to offer substitutable services or innovate independently.

92. Enforcers are beginning to respond to this issue. Assistant Attorney General Gail Slater, in her Fordham address, warned that "Google cannot be permitted to leverage its dominance in general search to the GenAI product space," emphasising the scale advantages of data and the likelihood that these dynamics will intensify with AI (U.S. DoJ, 2025[114]). Assessing vertical conduct in AI markets therefore requires distinguishing verifiable efficiencies from strategic integration that undermines contestability, consistent with the effects-based analysis adopted in recent enforcement practice (OECD, 2025[68]; CMA, 2024[115]; Krakowski, Luger and Raisch, 2022[26]). Refusals to grant access to essential AI inputs may constitute exclusionary conduct when such inputs are indispensable for effective competition and access to competitively critical data appears to be essential for AI competition:

> *The prospect of GenAI expands the competitive utility of data across every industry (..) Now every industry is a data industry. (…) The finite amount of publicly available data also means that there will be more and more of a premium on developing proprietary sources of data. Access to high-volume, high-quality, proprietary data is a significant competitive advantage that could prove extremely difficult for competitors to surmount. Strong demands for data may drive the forces of consolidation. For example, vertical integration may become more attractive, especially in industries where downstream businesses may have access to valuable and sensitive data like healthcare data.* Assistant Attorney Gail Slater *(U.S. DoJ, 2025[114])*

93. Alongside data, compute capacity represents another vertical restraint or bottleneck. High-performance compute (HPC) and cloud hosting are concentrated in a small number of global providers (also known as hyperscalers), which may tie model access to their infrastructure services, raising switching costs (OECD, 2025[3]; OECD, 2025[68]). The CMA has identified these as choke points, warning that

vertically integrated providers controlling both compute and applications may discriminate against rivals (CMA, 2024[67]). Such providers may try to attract complementary innovation from downstream users, while retaining control over their compute or APIs. This would replicate the dynamics observed in mobile operating systems (where app developers because dependent on the operating system). (Hagiu and Wright, 2025[65]) describe this as "cross-layer leveraging", where dominance in one segment (e.g., cloud or model access) extends across the stack. This could lead to systemic lock-in that would reduce the ability to multi-home and raise switching costs for users and developers.

3.2. An emerging concern: the attribution of liability

94. While some of the competition concerns raised by AI will resemble traditional theories of harm and will probably be solvable with the existing competition toolbox, the rise of AI systems, introduces novel challenges for competition enforcement, particularly in attributing conduct and establishing intent. Unlike traditional forms of co-ordination or exclusion, algorithmic and AI systems may produce anti-competitive outcomes autonomously, without direct human instruction or explicit agreement. Autonomous optimisation challenges traditional enforcement paradigms, requiring a shift in how responsibility is attributed.

95. AI systems can learn profit-maximising or exclusionary strategies through reinforcement learning or repeated interaction, even in the absence of deliberate co-ordination. This undermines conventional legal notions of intent and agreement. As the *Autorité de la concurrence* and *Bundeskartellamt* joint report on algorithms (2019[104]) noted, proving intent may be less relevant when competitive harm arises regardless of human intention. The report acknowledges the difficulty of attributing responsibility in cases where algorithms operate as opaque "black boxes," noting that "the complexity and opacity of algorithms may make it difficult to determine whether a certain conduct is anticompetitive and whether it can be attributed to a specific undertaking" (p. 24).

96. Compounding these challenges is the issue of explainability and accountability. Agentic AI further complicates the 'black box' problematic by continually updating parameters and adapting behaviour (Belcak et al., 2025[116]; Desai and Riedl, 2025[89]). This could potentially have procedural consequences: a lack of explainability might impede effective enforcement. Some authors suggest that such opacity may justify ex-post audit rights or mandatory disclosure of documentation that spans all the elements of the AI system, including, but not limited to, the models, its training data and algorithms, rather than new substantive prohibitions (Hagiu and Wright, 2025[65]). Another possibility would be technical co-operation between authorities and developers to facilitate interpretability (OECD, 2025[103]). Opacity does not create new offences, but it can hamper the attribution of accountability. Enforced transparency and auditability may become essential to sustaining competition law enforcement in AI-driven markets (Hagiu and Wright, 2025[65]).

97. The OECD's AI Principles, underscore that AI systems should be designed so that (i) their logic, data and decision-making can be suitably explained (explainability) and (ii) affected parties have meaningful access to challenge, appeal or correct outcomes (contestability). The first ensures transparency; the second ensures that transparency is actionable. Without contestability, explanations risk being purely descriptive and not leading to meaningful oversight, accountability or market contestation (OECD.AI, 2025[117]).

98. From a competition-policy perspective, ensuring contestability means enabling suppliers, users, and third-party challengers to verify, question or override embedded algorithmic decisions that may raise barrier, lock-in or exclusion risks. Explainability alone is a necessary but not sufficient condition for contestability.

99. Hagiu and Wright (2025[65]) argue that competition authorities must adapt their frameworks to account for autonomous optimisation. The OECD has similarly recommended evaluating foreseeability

and controllability – whether a firm could reasonably predict or prevent its algorithm's exclusionary or collusive behaviour (OECD, 2023[90]; 2025[103]). Authorities may need to assess design choices, governance processes, and oversight mechanisms, rather than relying solely on evidence of explicit intent. The CMA's 2021 report on algorithmic harms discusses how ineffective oversight of algorithmic systems can lead to consumer and competition harm. It highlights the need for regulators to develop audit tools and accountability frameworks, which could imply that firms may be held responsible for negligent deployment or lack of safeguards (CMA, 2021[118]).

100. The difficulties are likely to be further exacerbated with the rise of agentic AI, where autonomous agents may act on behalf of firms or individuals, or even independently, including in ways that resemble market co-ordination. This complicates attribution of harmful results, such as consumer welfare losses or exclusionary conduct. While agentic AI may foster pro-competitive dynamics in specific markets, it also raises forward-looking concerns around accountability, transparency, and the governance of interactions among autonomous systems – dynamics that are still not fully understood.

101. Agentic AI systems can raise complex liability questions, particularly when they act with a degree of autonomy that blurs the line between tool and actor. As these systems increasingly operate on behalf of firms or individuals – or even independently – the challenge lies in determining who is accountable for their outputs. Scholars highlight the need for governance mechanisms to mitigate risks linked to information asymmetry and discretion when such systems act on behalf of firms or individuals, or on their own volition (Kolt, 2024[119]; Desai and Riedl, 2025[89]). When agentic systems generate exclusionary or exploitative outcomes, the lack of direct human control complicates attribution, especially under legal frameworks that rely on intent or direct causality. This calls for a reassessment of liability standards, potentially shifting towards responsibility for design choices, oversight, and risk mitigation rather than traditional notions of intent.

102. Policy foresight exercises underline the potential systemic impact of agentic AI, but also its current limitations. The OECD's AI Capability Indicators report notes, "Agentic systems typically perform below level 3, indicating significant limitations on AI's ability to self-monitor and adaptively regulate its own reasoning" (OECD, 2025[120]). Nonetheless, the growing autonomy of agents could begin to extend their influence beyond narrow applications, reshaping online ecosystems and creating new intermediation layers between firms and consumers (Toner et al., 2024[82]). This suggests that, while agentic AI may foster contestability in specific markets, or even replace human agency in intermediation functions (such as travel agents), it also raises forward-looking concerns around accountability, transparency, and the governance of interactions among autonomous systems, which are still not fully understood.

3.3. Actions to support competition in AI-enabled downstream markets

103. To conclude the paper, this chapter discusses some of the levers available to policymakers and competition authorities to help ensure that AI-enabled markets remain competitive, drawing on OECD work and the experience of national competition authorities.

3.3.1. Enforcement actions

104. Enforcement remains a core tool for addressing anti-competitive conduct in AI-enabled downstream markets. While few cases have yet been concluded, several jurisdictions have initiated investigations or imposed remedies in adjacent markets with implications for AI.

Conduct cases

105. While there are no cases dealing specifically with AI, some NCAs have signalled the importance of monitoring how AI can be used by competitors not only for pro-competitive purposes but also to exploit consumers or exclude competitors. NCAs highlight the risks that can arise where AI is deployed in markets.

These include, for instance, the risk that "algorithms can allow competitors to share competitively sensitive information, fix prices, or collude on other terms or business strategies in violation of our competition laws; or the risk that algorithms may enable firms to undermine competition through unfair price discrimination or exclusion" (CMA, EC, DoJ, FTC, 2024[121]). Similarly, the Competition Commission of India (CCI) in its recent market study also flagged algorithmic collusion and price discrimination as emerging risks in downstream sectors such as retail, logistics and e-commerce. Its 2025 market study identified self-learning algorithms and parallel pricing systems as potential facilitators of tacit co-ordination, even in the absence of explicit agreements (CCI, 2025[113]). The *Autorité de la concurrence* and *Bundeskartellamt* (2019[104]) emphasised the need to scrutinise the effects of algorithmic systems, especially where they facilitate exclusionary or collusive outcomes without explicit co-ordination. Similarly, the G7 Ministerial Declaration (2024[122]) called for adaptive enforcement tools capable of identifying discriminatory ranking, algorithmic collusion, or self-preferencing, even in the absence of direct human intervention.

106. In the United States, the Department of Justice's remedies in the Google Search case required data sharing with AI competitors, recognising that search data are an essential input into generative AI models (U.S. DoJ, 2025[123]). Similarly, competition authorities in G7 jurisdictions have examined algorithmic pricing practices, including hub-and-spoke arrangements and tacit co-ordination, under traditional theories of harm (OECD, 2025[103]).

107. Enforcement may also be required to address bundling or tying of AI services with cloud infrastructure, particularly where access to compute is conditioned on the use of affiliated AI models (OECD, 2025[3]). The French *Autorité de la concurrence* has identified a range of risks associated with such practices in its sector inquiry into generative AI. Major digital firms, especially those vertically integrated across cloud infrastructure and AI model development, may leverage their control over compute to favour their own AI offerings, either through technical lock-in, preferential access, or exclusive agreements. The Autorité notes that such practices could constitute abuses of dominance, particularly where they restrict access to key inputs like GPUs, training data, or skilled labour, or where they involve tying AI services to cloud usage in ways that foreclose rivals or entrench incumbents (Autorité de la concurrence, 2024[70]). The CMA had similar findings, and proposed remedies to address switching barriers in cloud services, including obligations to improve interoperability, reduce egress fees, and prevent discriminatory treatment of third-party services. These remedies are particularly relevant in AI markets, where access to scalable compute is a prerequisite for model training and deployment (CMA, 2024[115]; CMA, 2023[46]).

Merger control

108. Merger control is also a critical tool for addressing structural risks in AI-enabled markets. Acquisitions can be a powerful way for digital incumbents to either become gatekeepers or strengthen their dominant position, possibly extending it to adjacent markets (Nicoletti, Vitale and Abate, 2023[124]). As highlighted in the CCI's market study, acquisitions and partnerships involving AI firms may raise competition concerns, particularly where they involve exclusive access to data, compute, or intellectual property. Even minority investments can confer strategic influence over target firms, requiring careful scrutiny (CCI, 2025[113]). Similarly, exclusive cloud supply agreements, distribution arrangements, and IP licensing may create dependencies that foreclose rivals or entrench dominant positions (CCI, 2025[113]). Competition authorities have emphasised the need for case-by-case analysis to assess whether such transactions harm contestability or innovation. Existing merger control frameworks are normally equipped to address these risks, but the analytical framework might need to be broadened to incorporate assessments of data access, innovation incentives, and platform dependencies.

3.3.2. Competition advocacy and market monitoring

109. Competition enforcers need robust information on how AI-systems are reshaping competition dynamics. Given the rapid pace of AI adoption, market studies and monitoring tools are useful to assess emerging risks. These instruments allow authorities to gather evidence, consult stakeholders, and evaluate whether enforcement, regulatory adjustments or voluntary commitments are appropriate. The OECD and JFTC highlight the importance of proactive monitoring tools, such as sectoral mapping, adoption surveys and the use of AI-driven analytics to identify emerging patterns of market concentration, especially where conventional datasets lag behind market developments (JFTC, 2025[105]; OECD, 2024[50]).

110. To assess if AI adoption may give rise to structural risks, competition authorities could also consider launching market studies. These can explore, in greater depth, the implications of data control, interoperability restrictions or integration of AI assistants within digital ecosystems. Market studies are a flexible instrument: they allow authorities to gather evidence, consult stakeholders, and assess whether competition law enforcement, regulatory adjustments or voluntary commitments are most appropriate (OECD, 2018[125]). Several national competition authorities, including (but not limited to) the CMA, the French *Autorité de la concurrence*, the CCI, and the ACCC have already carried out such studies to shed light on competition issues in digital and AI-related markets, including foundation models, advertising, and digital ecosystems (CMA, 2023[92]; CMA, 2024[67]; ACCC, 2025[93]). These studies have identified structural risks such as data bottlenecks, interoperability restrictions, and integration of AI assistants into dominant platforms.

111. Competition advocacy also plays a critical role in shaping policy debates around AI and market design. Advocacy enables competition authorities to proactively highlight emerging risks and promote regulatory frameworks that support contestability without stifling innovation. OECD work has consistently emphasised the importance of interoperability standards, transparency obligations, and safeguards against discriminatory access to key AI inputs such as data, compute, and talent (OECD, 2023[126]; 2025[68]; 2021[127]). National authorities have also used advocacy to raise awareness and guide policy development. For example, the Portuguese Competition Authority has published a series of short papers on generative AI, warning of “competition risks regarding access and use of data,” the potential for “lock-in effects” from closed foundation models, and the impact of talent concentration and labour mobility restrictions on innovation and market entry (AdC, 2024[11]). These publications serve as early-stage policy interventions, aimed at shaping the conditions under which AI ecosystems evolve. More broadly, advocacy can take the form of public consultations, market studies, or guidance documents that inform legislative and regulatory processes, promote pro-competitive standards, and ensure that emerging AI markets remain open, interoperable, and innovation-friendly.

3.3.3. Regulation

112. Views differ across jurisdictions on the complementary role of regulation in ensuring competitive and open AI markets. In jurisdictions which have adopted ex ante regulation of digital market, the aim of the regulation was not to replace ex post enforcement, but ex ante regulatory frameworks can help provide clarity and predictability for market players, particularly in fast-moving digital environments where market power may become entrenched before traditional enforcement tools are able to intervene effectively. While this paper does not enter into the debate of whether AI should be subject to regulation, the experience of regulation of digital platforms has shown that ex ante measures can complement enforcement by addressing gaps where reactive tools have proven too slow or limited to prevent harm.

113. Measures that could prove useful to support competition in AI-enabled market would include licensing terms for accessing data, auditability of models and their architecture, and interoperability between systems. Such measures could potentially become critical to ensuring market contestability. On the contrary, restrictive licences, unilateral withdrawal of access, or opaque training practices can foreclose

downstream rivals. The *Autorité de la concurrence* has warned that "restrictive licensing terms or opaque access conditions" for foundational AI inputs such as data and compute may lead to exclusionary effects, particularly when imposed by vertically integrated firms. Similarly, the CMA, in its cloud infrastructure market investigation, identified interoperability barriers and discriminatory licensing as key risks to competition, especially where access to compute is bundled with affiliated AI services. Potential instruments to remedy against such practices would include imposing transparency obligations in the AI stack or in-house models, standard-setting initiatives to facilitate interoperability, and finally enforcement against discriminatory licensing (Autorité de la concurrence, 2024[70]; CMA, 2024[67]; OECD, 2021[127]).

3.3.4. Sector and international co-operation

114. International and cross-sectoral co-operation is essential to address competition risks in AI-enabled downstream markets. The global scale of compute infrastructure and foundation model development means that national enforcement alone is unlikely to be sufficient to address concerns related to cross-border market power or multi-jurisdictional exclusionary conduct. Moreover, the complexity and opacity of AI systems – particularly those embedded in regulated sectors – can make it difficult for any single authority to detect and address anti-competitive outcomes in isolation.

115. In many sectors – such as health, finance, energy, and transport – sectoral regulators oversee access to critical infrastructures and datasets, including electronic health records, financial transaction data, smart grid information, and mobility platforms. These regulators define the technical and legal conditions under which such data can be accessed, shared, or reused. While these frameworks are typically designed to protect privacy, safety, or system integrity, they can also shape the competitive dynamics of AI markets. For example, if access to a key dataset is limited to a small number of incumbents, or if licensing terms are overly restrictive, new entrants may be unable to develop or deploy competitive AI solutions (OECD, 2019[128]). In such cases, the absence of co-ordination between competition and sectoral authorities may inadvertently reinforce market concentration. OECD analysis has highlighted the importance of aligning access regimes with competition principles, ensuring that safeguards do not become de facto barriers to entry (OECD, 2025[68]).

116. Sectoral regulators also influence market structure through their role in setting technical standards, certification requirements, and procurement criteria. These instruments can affect the interoperability, auditability, and deployability of AI systems. For instance, explainability or safety requirements may determine which models are eligible for use in a given sector, potentially favouring certain architectures or providers. Co-ordination with competition authorities can help ensure that such requirements are implemented in ways that support innovation and do not unintentionally favour vertically integrated firms. In this context, co-operation is not only about avoiding regulatory conflict but about jointly identifying and mitigating structural risks that may not be visible from a single institutional perspective.

117. International co-operation is equally important to align approaches to AI regulation, enforcement, and market monitoring. Annual international competition events and conferences, and NCAs' bi-lateral or multilateral engagements with international partners have help sharing learning and experience, and set up joint initiatives to address common challenges. Co-operation can support the development of common standards, facilitate cross-border enforcement, and ensure that AI markets remain open and contestable. This includes collaboration on issues such as technical standards, data governance, and competition assessments of global AI providers.

4 Conclusion and future directions

118. AI adoption in downstream markets presents both opportunities and challenges for competition. On the one hand, AI systems, in particular generative and agentic models, can lower barriers to entry by reducing labour and operational costs, enabling product differentiation and supporting innovation. So far, these effects are most visible in sectors with high exposure to cognitive tasks, such as professional services, software development and customer support. Modular and "plug-and-play" AI tools may allow smaller firms to scale more efficiently, while fine-tuning capabilities can support domain-specific innovation.

119. On the other hand, the competitive impact of integrating AI systems in downstream markets appears to be highly context dependent. Structural advantages in data, compute, and integration capacity may allow incumbents to capture or hold on to disproportionate gains. Where access to models or data is restricted, or where interoperability is limited, downstream contestability may be reduced. The paper highlights that model access, rather than openness alone, is likely to be a key determinant of differentiation and innovation. Similarly, data access – both upstream and operational – can shape firms' ability to adapt AI systems to their needs. These dynamics may reinforce existing market power or create new bottlenecks, particularly in vertically integrated AI stacks.

120. From an enforcement perspective, AI systems may amplify traditional concerns such as collusion, exclusionary conduct, and foreclosure, while also introducing new challenges around attribution, transparency, and strategic adaptation. Generative and agentic AI systems may complicate the assessment of effects and liability, potentially requiring of competition authorities to also consider issues such as data governance, model explainability and design choices. The paper outlines how the use of generative AI may amplify risks such as personalised and dynamic pricing or vertical leveraging, and discusses how enforcement, advocacy, and regulation can help address these concerns.

121. To ensure that AI-enabled markets remain open and competitive, a multi-pronged approach seems to be needed. Enforcement may have to adapt to the realities of autonomous and opaque systems, potentially requiring a shift towards effects-based reasoning or even the development of new investigative tools. Competition advocacy and market studies can help identify emerging risks and inform regulatory design. Sectoral co-operation will be essential to align standards, support fair access to key inputs, and prevent regulatory fragmentation. Ultimately, the competitive impact of AI will depend not only on the technology itself, but on the institutional frameworks that govern its deployment and use.

122. Looking ahead, given the fast pace of developments in the sector – many of the references that this paper relies on were publishing during the time of writing – further empirical research is needed to assess sector-specific competitive impacts, particularly in health, finance, logistics, creative industries and professional services, where AI may both expand demand and reshape labour pipelines (Above The Law, 2025[129]). For instance, AI image generation is increasingly a substitute for stock imagery (concept art, product mock-ups, backdrops) and an input to, or substitute for, creative ideation pipelines. In July 2025, the fashion brand, *Guess*, sent shock-waves through the media world when its advertising in the magazine *Vogue*, featured a model generated by AI (BBC, 2025[130]). No human featured in their advertising campaign. Quite apart from the questions this may raise on ethical or cultural grounds, this demonstrates the power and potential of GenAI to structurally alter the competition dynamics of a sector.

123. Emerging questions around agentic AI also require close monitoring, as these systems may both lower search costs and risk biased steering of consumer choices (LinkedIn/Ipsos, 2025[55]). Comparative work across jurisdictions, such as the JFTC's 2025 mapping of competition authority initiatives, offers valuable insights into common challenges and approaches.

124. At international level, co-ordination will be essential to address concentration risks arising from the global scale of compute and foundation models. Ensuring open and contestable markets for AI will therefore require a mix of national enforcement, cross-sectoral regulatory safeguards, and international co-operation.

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Notes

[1] In the context of AI and machine learning, the term "corpora" (plural of *corpus*) refers to large and structured sets of data, typically text, that are used for training and evaluating models, especially in natural language processing (NLP). They are important because Corpora are used to train AI models to understand and generate human language; evaluate model performance on tasks like translation, summarisation, sentiment analysis, or question answering; and fine-tune model for specific domains (e.g., legal, medical, financial). The are difficult to replicate for new entrants and constitute a significant barrier to entry.

[2] Company, AI-system and sector examples used in this paper are only meant to be illustrative. They are all drawn from public sources and are included to provide context, and should not be interpreted as endorsements.

[3] Field experiments at major firms likewise report that less experienced developers achieve disproportionate productivity gains when supported by AI assistants (Cui et al., 2024[19]).

[4] OECD surveys show that smaller firms in digitally intensive sectors have higher adoption rates of AI than less digitalised firms, and that adoption often correlates with entry and survival in competitive markets (Calvino, Haerle and Liu, 2025[7]).

[5] One estimate for enterprise-grade implementations of AI systems for customer support says they typically require between USD 100 000 and USD 2 million in initial expenditure, including platform setup and licensing fees. However, depending on the volume of customer queries (in this estimate, the volume was around 55 000/year), these costs may be recovered within a relatively short period of around six months.

[6] Business Process Outsourcing (BPO) refers to the practice of contracting specific business functions or processes to external service providers, often in another country, to reduce costs and improve efficiency. These outsourced processes are typically non-core but essential operational tasks, such as customer support, data entry, payroll processing, or IT services. For example, a telecommunications company might outsource its customer service operations to a call centre in the Philippines or India to benefit from lower labour costs and 24/7 coverage. Similarly, a bank might outsource its back-office functions, such as loan processing or compliance checks, to a specialised service provider that can perform these tasks more efficiently at scale.

[7] Randomised experiments show substantial time savings and quality improvements on mid-level professional writing tasks when workers use a general-purpose assistant, with the magnitude varying by task and baseline skill (Noy and Zhang, 2023[17]; OECD/BCG/INSEAD, 2025[27]).

[8] In a natural experiment, GenAI reduced the average price of commissioned digital artwork by 64%, while increasing order volumes by 121%, indicating a downward shift in marginal and average production costs as automation replaced labour-intensive creative tasks (Zhang, Yuan and Xiong, 2023[155]). The authors conclude that using AI can shift the supply curve outward, reducing average operational costs.

[9] It should be noted that these findings are survey based. While AI has potential to improve a vast array of uses, including forecasting included, it still makes mistakes. Some evidence seems to suggest, for example, that it might be better at forecasting modal or common events, for instance related to the weather, but not so good at extremes. https://arxiv.org/abs/2508.15724

[10] Nubank, a digital financial services platform now covering Brazil, Mexico and Colombia, has used generative AI copilots to automate internal compliance and expand customer service capacity through rolling out a call-centre pilot, allowing it to compete with established banks despite limited physical infrastructure (Ashton, 2025[132]). Nubank's AI-powered assistant can resolve 55% of initial enquiries without escalating to a human agent, handling over 2 million monthly chats and reducing chat response time by 70%, responding 24 hours a day (OpenAI, 2024[133]).

[11] The authors introduce a systematic methodology to evaluate exposure and automation potential across United States occupations. While the study focuses on the United States, the findings related to task automation and AI exposure is likely to be widely applicable across other economies, and relevant for the discussion about AI-adoption.

[12] (Eloundou et al., 2024[12]) find that tasks requiring programming or writing show the highest exposure to **AI automation**, whereas those requiring scientific reasoning, critical thinking and active learning remain less susceptible. Education-wise, higher **exposure** was found in jobs requiring bachelor's or master's degrees, whereas jobs requiring extensive on-the-job training continue to depend primarily on human skills: "Jobs with no on-the-job training or only internship or residency required appear to yield higher income but are more exposed to LLMs." (Eloundou et al., 2024, p. 34[12]).

[13] Other occupations include education and training: generative AI tools are increasingly used to automate lesson preparation, grading support and content generation, illustrating how exposure does not necessarily imply full automation but rather task augmentation. In India, for instance, small education-technology firms draw on publicly available or firm-owned materials to generate course content and adaptive assessments, substantially reducing production costs and time-to-market (Digital Futures Lab, 2022[146]). These developments align with (Eloundou et al.[12])'s findings that teaching and writing-intensive occupations are highly exposed to LLM capabilities, yet the technology primarily complements rather than replaces skilled educators for now.

[14] In logistics and retail, operators integrate artificial intelligence into demand forecasting, stock management and routing through cloud modules, enabling small firms to replicate efficiencies once available only to incumbents with in-house analytics. ShopriteX in South Africa has scaled its grocery delivery services through AI-enabled logistics optimisation (Dicey, 2025[81]; Nishar, 2024[82]).

[15] The study was published in 2025, but the survey was conducted in 2022-23.

[16] MIT also identifies additional organisational bottlenecks, including poor workflow integration, lack of memory and learning in AI systems, and low tolerance from users for "static" tools compared to flexible consumer LLMs (MIT, 2025[45]).

[17] CMA Decision on the case No. 50223 12/08/2016.

[18] As established in Case T-41/96 Bayer, ECLI:EU:T:2000:242

[19] The Commission's 2022 commitment decision in Amazon Buy Box (AT.40703), linked to Amazon Marketplace (AT.40462), addressed alleged self-preferencing in Amazon's automated Buy Box and Prime eligibility systems, which the Commission found tended to favour Amazon Retail and Fulfilment by Amazon sellers. While no infringement was established, Amazon accepted binding commitments to ensure non-discriminatory Buy Box display (including a "Second Offer"), and a ban on using non-public seller data, with accountability extending explicitly to its automated systems.

[20] Other bottlenecks in the AI stack, such as cloud computing or access to infrastructure, are discussed in-depth in (OECD, 2025[4]) and (OECD, 2025[3]).

[21] A proprietary data ecosystem like LinkedIn's professional graph of 1.2 billion members and 60 million firms, illustrates how control over strategic data assets can sustain incumbents' positions and remain a source of competitive advantage (LinkedIn/Ipsos, 2025[55]).