The AI Value Chain: Research and Policy Priorities

Bennett Institute for Public Policy & Organisation for Economic Co-operation and Development (OECD)

6-7 May

Online – MS Teams Townhall

Tuesday 6 May 2025

10:00 - 11:00 | Technical Keynote
How should policymakers think about the AI value chain? What technical advances in AI are shaping its capabilities, and what are the emerging risks and opportunities?

Break

11:15 - 12:45 | Hardware & Compute
What roles do hardware and compute play in the AI value chain? What are the dependencies, and how do they shape policy priorities?

Lunch

13:45 - 15:15 | AI Innovation & Diffusion
Where are the key areas of and trends in AI diffusion, and what are the implications for policy?

Break

15:30 - 17:00 | Use Cases
How might AI be used in the public and private sectors? How do the economic incentives and societal implications interact?

Wednesday 7 May 2025

10:00 - 11:00 | Economic Keynote
How might progress in AI be measured, and in a way that promotes public value?

11:00 - 13:00 | AI's Economic and Societal Implications
Given the current and potential future uses of AI, how can policymakers not only manage the risks of AI but also ensure that it benefits society as a whole?

The schedule is tentative and subject to change.

Workshop Background and Framing

As developments in and use of artificial intelligence (AI) rapidly advance amidst a complicated economic, social, and political backdrop, governments worldwide have recognised that traditional policy measures may not be fit for purpose – and consequently, there may be challenges in aligning rapid developments in AI with broader social objectives. However, what to do about this challenge remains an open question. This concept note frames some of the key issues emerging around the AI value chain to surface opportunities, gaps, and tensions that may provide fruitful discussion points for future research and policy work.

It supports a workshop convened by the Bennett Institute for Public Policy at the University of Cambridge and the Organisation for Economic Co-operation and Development (OECD). It aims to identify priority areas for policy-oriented research on the AI value chain. By bringing together technologists, economists, and social scientists to identify research gaps and what is needed to inform policymaking. It examines hardware and compute, innovation and use cases, and the broader economic and societal implications.

The AI Value Chain

The discussion centres around the AI value chain, which considers how AI accrues values over "the AI system... [which] encompasses the following phases that are not necessarily sequential: planning and design; collecting and processing data; building and using the model; verifying and validating; deployment; and operating and monitoring" (OECD 2022). The components discussed here broadly encompass infrastructure, models, and applications and use cases (though definitions and conceptualisations may vary), as well as the enabling environment.

The infrastructure layer forms the foundation of the AI stack, encompassing the hardware and compute capacity, as well as cloud platforms that enable the storage, processing, and running of AI workloads and services. Compute hardware includes chips and specialised processors – for example, graphics processing units (GPUs), field-programmable gate arrays (FPGAs), and application-specific integrated circuits (ASICs) – that provide the computational power necessary for training and running AI models (Khan 2020). The demand for this hardware has grown alongside the demand for AI, and advances in chip design and production have enabled exponential increases in processing efficiency (Vipra and Myers West 2023; Coyle and Hampton 2024; Heim et al. 2024). Chip advancement is seen as especially important as models become larger and more computationally intensive (Clark 2024). In addition, cloud platforms have a growing role within this layer, given that they offer more flexible and scalable access to computing infrastructure (OECD 2023a). Many governments have recognised the strategic importance of compute infrastructure and reliable semiconductor supply chains – and, accordingly, have moved towards industrial policy initiatives aimed at bolstering compute capacity (Khan 2021; Shearer, Davies, and Lawrence 2024).

One question is whether policy should encourage research, development and ultimately production of alternative hardware, particularly more energy-efficient compound semiconductors, as an element of industrial policy. This may also include consideration of the extent of diversification countries aim to achieve in the chips supply chain, at which costs, and how actions might be coordinated to avoid a subsidy race. Another question relates to the development of national cloud infrastructure.

The model layer builds on this infrastructure, representing the algorithms and machine learning models that power AI systems. Foundation models – "AI models designed to produce a wide and general variety of outputs...[that] are capable of a range of possible tasks and applications, such as text, image or audio generation" – have been the focus of most policy efforts (Jones 2023). Such models can be standalone tools and additionally underpin the range of tools we have come to associate with AI (ibid). While models vary, they can be broadly categorised according to their downstream access levels. Some are open-source – for example, Stable Diffusion by Stability AI – or proprietary and driven by API access – like those developed by OpenAI, Anthropic, or Google DeepMind (though the distinctions can be blurred in practice) (Küspert, Moës, and Dunlop 2023). In addition, there is a growing role for model hubs and repositories, which centralise access to pre-trained models and associated tools – often with the goal of adapting generalised models to domain-specific tasks (Keller 2023).

Policy issues at the model layer include whether there is a viable role for alternative model development and competition policy given the complex relationships between (mainly US) providers of foundation models.

The application layer is perhaps the most visible of the AI value chain – where models are operationalised to deliver services across various use cases and domains. In addition to those mentioned above, applications can range from predictive analytics tools used in business intelligence (Praful Bharadiya 2023) to computer vision systems deployed in manufacturing (Zhou, Zhang, and Konz 2023) to natural language processing and sentiment analysis models used for virtual assistants (Adamopoulou and Moussiades 2020). There are also several potential and active domain-specific uses. For example, AI applications have been extensively explored in healthcare and can facilitate diagnostic imaging, drug discovery, and personalised medicine (Haleem, Javaid, and Khan 2019; Shaheen 2021). There have been a range of actualised and envisioned uses in other domains, including, but not limited to, education (Zhai et al. 2021), financial services (Hentzen et al. 2022), and environmental science (Hickey 2020; Nevo et al. 2022).

Competition policy – specifically, the need to ensure applications can scale and enter or enable markets without being acquired or inhibited by large tech companies – is a key issue at this layer, as are policy instruments to derisk investment and enable innovators to develop viable business models.

Beyond the component parts of AI, the value chain also includes complementary aspects such as human capital, enabling infrastructure, and, in particular, data.

There has been growing awareness, for instance, of the need for a skilled workforce to manufacture the component parts of AI systems, develop and train models, and use the AI models being rolled out in various industries (Borgonovi et al. 2023), in addition to foundational skills and critical thinking. Relatedly, a jurisdiction's ability to use AI and remain competitive heavily depends on its enabling infrastructure – and a related understanding that global gaps may be exacerbated without investments in infrastructure (Heim et al. 2024). Finally, AI systems are only as good as the data they are trained on, creating an important role for data governance and maintenance (Janssen et al. 2020).

While this is a simplified representation, it highlights the interdependencies and complexities in the value chain. Each layer involves diverse actors, ranging from hardware manufacturers and cloud providers to research institutions, software developers, and industry end-users. Progress in one layer often catalyses advancements in others. For example, improvements in hardware efficiency enable the training of more complex models, which in turn facilitate the development of new applications. At the same time, constraints or bottlenecks – such as limited access to compute infrastructure or the scarcity of high-quality training data – can stand in the way of progress. Relatedly, it spotlights the resource intensity of the AI value chain, from raw materials for semiconductor production to energy for running computationally intensive models. And it foregrounds the different incentives and associated approaches of actors within the value chain.

Trends in AI Diffusion

Though AI is not a new technology, its development and use have accelerated, especially via the mainstreaming of generative AI. As its use has expanded, so too have the attempts to track and measure its diffusion.

Studies of AI use find that large firms use AI more widely than others, likely due to greater resources to invest in complementary assets like digital infrastructure and ICT skills – which can lead to entrenched gaps between smaller and larger firms (Calvino and Fontanelli 2023). Relatedly, AI diffusion is uneven across sectors, with higher adoption rates in ICT and Professional Services (Calvino and Fontanelli 2023; Calvino et al. 2022), indicating that AI's full potential is yet to materialise across all economic sectors – especially those seen as having significant social value like healthcare and education. These trends have important implications, as firms that use AI are generally more productive (ibid). Overall, these trends in AI diffusion may contribute to the persistent gaps observed between stated desires for AI and the actual outcomes of its use (Montgomery et al. 2024). As such, governments are seeking proactive policy measures that can shape the technology's trajectory towards greater societal benefit.

Key Policy Issues

As outlined, the AI value chain is both complex and unevenly diffused across countries and firms, adding significant complexity to the policymaking landscape. AI has become a cross-cutting issue in the emergence of industrial policy activism and a vertical sector of interest in some OECD countries.

Many jurisdictions remain in the early stages of formulating AI strategies and policies, and academic as well as policy-focused literature has begun to converge around three core questions: (1) where governments should focus their attention within the AI value chain, (2) what policy measures they should employ, and (3) how policymaking and policy evaluation might evolve as AI continues to present new opportunities and risks.

First, there is the question of where governments should focus their attention. Governments worldwide are increasingly concerned about maintaining and enhancing their competitiveness in the digital era. As a result, they have begun to frame AI development within broader industrial policies and national strategies. Within these efforts, there has been significant debate surrounding which aspects of the AI value chain should be prioritised.

The expansion of AI's development is happening amidst a complicated geopolitical backdrop, and one that has seen a resurgence of industrial policy. Thus far, industrial policy initiatives related to AI have, tended to emphasise hardware and compute infrastructure (Alayande and Turobov 2024; Ilyina, Pazarbasioglu, and Ruta 2024). International organisations have also underscored the importance of compute infrastructure, recommending benchmarking exercises to assess regional capabilities and facilitate more equitable access to these enabling resources (OECD 2023a). While chips and computational capacity have attracted significant policy attention, other components of the AI ecosystem remain comparatively under-emphasised. Cloud platforms, for instance, are an increasingly important part of the AI value chain. Yet, few strategies and policies explicitly address governance models, pricing structures, data localisation issues, or the competitive dynamics that shape cloud markets (Van Der Vlist, Helmond, and Ferrari 2024).

In addition, one of the most active areas of debate is whether policies should be targeted at general-purpose AI development (e.g., broad support for fundamental research and compute infrastructure) or oriented toward sector-specific applications in areas like healthcare, agriculture, or smart manufacturing (Trajtenberg 2018). General-purpose interventions may generate widespread spillovers across the economy, but sector-specific measures can yield more immediate, visible gains and address strategic priorities or pressing societal needs (ibid). Domain-specific approaches might also be seen as more fruitful grounds for international co-operation relative to policies targeting infrastructure and general-purpose AI development, which may prioritise national interests (Turobov, Coyle, and Harding 2024). Parallel debates are occurring around industrial policy (Criscuolo et al. 2022; Rodrik 2004; Warwick 2013).

Once AI systems are developed, their degree of diffusion among businesses remains a key factor of policy attention, notably considering the significant potential of AI for productivity and economic growth (Calvino and Fontanelli 2024; Filippucci, Gal, and Schief 2024). While official statistics still highlight low shares of AI use by enterprises, especially concentrated among larger businesses and in the ICT sector (Calvino et al. 2024; OECD 2024b), the most recent advances in generative AI may point to an increasingly general-purpose nature of the technology, as well as bring new measurement challenges. A policy mix encompassing a range of complementary enablers of AI diffusion – including skills, digital capabilities and digital infrastructure – and ensuring that the use of AI is innovative and trustworthy and respects human rights and democratic values – in line with the [OECD AI Principles] – can help foster an inclusive digital transformation as AI spreads among firms (OECD 2024a).

Indeed, beyond the technical realm, some scholars advocate for policies that strengthen some of the foundational layers of the AI value chain, particularly data governance and workforce development, as a prerequisite to all other efforts. For some, improving data availability, quality, interoperability, and governance standards may ultimately prove as important as investing in infrastructure (Janssen et al. 2020). Similarly, building a skilled workforce – comprising not only technical AI experts but also domain specialists, data managers, and policymakers who can interpret and apply AI outputs responsibly – is seen as critical to realising the potential gains of the technology (Borgonovi et al. 2023). Conversely, without careful attention and intervention, some argue, it is likely that more jobs will be displaced than augmented and that AI will increase inequality (Tyson and Zysman 2022).

In fact, the extent to which AI – and in particular *generative* AI – may replace tasks that were not automatable in the past brings new challenges for labour markets and inequalities (Calvino and Criscuolo 2024; OECD 2023d). A lively debate discusses whether more or less automation is preferable, the differences between augmentation in some tasks and automation in others, the extent to which policymakers should steer the development of AI, and the promises and perils of humanlike artificial intelligence (Agrawal, Gans, and Goldfarb 2023; Acemoglu and Johnson 2023; Brynjolfsson 2022). Available evidence does not highlight significant negative employment effects due to AI (OECD 2023d). In terms of job quality and inclusiveness, while AI specialists seem to earn significant wage premia (Green and Lamby 2023; Manca 2023), wages for many workers affected by AI often remained unchanged (Milanez 2023). Furthermore, AI does not yet seem to have significant impacts on the gaps between high and low-wage occupations, although it may be reducing wage inequality within occupations (Georgieff 2024). AI also appears to be associated with greater job satisfaction, while risks, e.g. in terms of increased work intensity or bias, still remain at the centre of the policy debate (Broecke 2023; Lane, Williams, and Broecke 2023; Lorenz, Perset, and Berryhill 2023).

Next, there is active debate surrounding what policy measures governments should use. Once governments identify priority areas within the AI value chain, the next question is how best to intervene.

At a high level, there has been a push towards creating national strategies for AI (OECD 2021). For some, national strategies represent an opportunity to align efforts across a given jurisdiction and set a vision for AI that is aligned with maximising social value (Montgomery et al. 2024). However, some argue that some strategies are not fit for purpose (for example, copied from elsewhere) and are largely tools of political narrative and have not translated into meaningful policy and regulatory outcomes (Bareis and Katzenbach 2022).

For example, an area that remains underdeveloped in current policy frameworks is the question of model ownership and governance – though some efforts are already underway (see, for example, the OECD AI Principles and OECD 2023c, 2023b). As large-scale language and vision models underpin a range of applications, questions arise about who controls the models, who can adapt or fine-tune them, and how their performance and biases are monitored and regulated. Some jurisdictions are beginning to explore policies that encourage open-source model development and the creation of publicly funded data and/or model repositories (Massey et al. 2024). Others are investigating data trusts, data cooperatives and corporate and contractual models as mechanisms for accountability (Ada Lovelace Institute and AI Council 2021).

Moreover, competition policy must adapt as new actors enter the AI ecosystem –from platform-based service providers to specialised AI start-ups (Smuha 2021b). Concerns about market concentration, control over crucial inputs (such as training data or compute resources), and potential anti-competitive behaviours have sparked debates over how antitrust enforcement and competition rules should evolve (Vipra and Korinek 2023). Policymakers may need to develop new metrics and analytical tools to assess market power in an AI-driven economy (Dafoe 2018). This is, again, an area of intersection with the active debates in industrial policy (Aghion et al. 2015; Aiginger and Rodrik 2020).

Finally, there is the question of how policymaking and its evaluation might evolve given the new opportunities and risks AI presents.

AI cuts across multiple policy realms, making domestic and international coordination complex. Domestically, policymakers must "join up" government efforts across different policy areas to ensure that infrastructure development, data governance, workforce training, and sectoral initiatives reinforce rather than undermine each other; however, this has been a longstanding and well-documented challenge (Coyle and Muhtar 2022; Peters 2018; Webb 2019). Internationally, some see engagement with multilateral organisations, standard-setting bodies, and bilateral initiatives as important mechanisms for harmonising regulations, reducing trade frictions, and preventing a regulatory race to the bottom. However, there are several international efforts, all with varying levels of coordination and relationships with one another (Turobov, Coyle, and Harding 2024). While there is a significant amount of complementarity, researchers find that opportunities for coordinated action remain (ibid).

Public trust is also a key concern across the AI value chain, particularly regarding data. Recent government surveys have shown differential public trust levels and preferences regarding data sharing in public services, academic research, and private sector (particularly social media) companies (Department for Science, Innovation and Technology 2024). As technologies evolve, policymakers are actively grappling with how to involve the public in governance discussions and integrate technology into public services to facilitate greater trust.

Existential questions also remain. Should governments adopt a harm- or risk-oriented approach that focuses on preventing negative externalities, such as algorithmic discrimination and bias or environmental harm (Acemoglu 2021; Smuha 2021a)? Or should policies prioritise promoting innovation to ensure global competitiveness, even if it means accepting a higher degree of uncertainty and potential risks (Horowitz 2018)? Others argue for a resilience-based paradigm emphasising the capacity to withstand shocks – such as technological disruptions, supply chain vulnerabilities, or geopolitical tensions – in a rapidly shifting digital landscape (Janjeva et al. n.d.). Jurisdictions must proactively choose their orientation, given that trade-offs will necessarily exist in AI policymaking (Coyle and Weller 2020).

Conclusion

This concept note frames some of the key considerations and active debates within the AI value chain as a starting point for identifying the most pressing questions for policy-oriented research. Building on existing work, this roundtable aims to:

- Identify trends from a technical, economic, and social science perspective
- Determine priority research gaps relevant to policymaking, especially those that cut across use cases
- Consider what data, partnerships, and funding are needed to fill these gaps
- Outline the concrete steps needed to make the proposed research a reality

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