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IS GENERATIVE AI A GENERAL-PURPOSE TECHNOLOGY?

IMPLICATIONS FOR PRODUCTIVITY AND POLICY

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Is generative AI a general-purpose technology? Implications for productivity and policy

Flavio Calvino[1], Daniel Haerle[1], Sarah Liu[1]

The rapid rise of generative AI has sparked discussions about its potentially transformative effects and whether the technology will bring significant benefits in the form of widespread productivity increases. Through a review of theoretical literature and early empirical evidence, including novel descriptive analysis, this study suggests that generative AI has considerable potential to qualify as a new general-purpose technology (GPT). Despite the early evidence, generative AI appears to exhibit the defining characteristics of GPTs: i) pervasiveness, ii) continuous improvement over time and iii) innovation spawning. While productivity gains may not materialise immediately, the evolution of earlier GPTs seems to provide encouraging signs that generative AI could lead to substantial improvements in productivity in the future, notably through the innovation-spawning channel. The full realisation of generative AI's productivity potential in the long-term will depend on the implementation of relevant policies.

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Executive Summary

The recent rise in generative AI's applications and diffusion have highlighted unprecedented technological advances and mainstreamed some of the technology's growing potential. As businesses and governments focus their efforts on these developments, and the related governance issues, discussions have emerged about generative AI's potentially transformative effects and whether the technology will bring significant benefits in the form of widespread productivity increases and substantially higher living standards and well-being.

Historically, transformational technological innovations like the steam engine, electricity, and computers had profound impacts due to their general-purpose nature, permeating various economic processes and contributing to widespread productivity growth. While previous studies have attempted to evaluate the aggregate productivity effects of AI more broadly, this paper specifically analyses whether *generative* AI is a general-purpose technology, and its broader economic and social implications.

Through a review of theoretical literature and early empirical evidence, including novel descriptive analysis, this study suggests that generative AI has considerable potential to qualify as a new general-purpose technology (GPT). Despite the early stage of technology diffusion upon which the discussion and evidence presented are based, generative AI appears to exhibit defining characteristics of GPTs, notably i) pervasiveness, ii) continuous improvement over time, and iii) innovation spawning. Attaining these three defining GPT characteristics in combination is essential in enabling a considerable economic impact of the technology, as generative AI's potential critically depends on the extent to which it can achieve widespread use that also generates substantial spillover effects and fosters innovational complementarities, raising overall productivity and driving economic growth.

In terms of pervasiveness, the applications of generative AI innovation, despite being prevalent in software, span across a considerable number of other areas, ranging from life and medical sciences to banking and finance. While the most recent official figures on usage among firms appear still limited and concentrated in certain sectors, adoption among individuals appears higher, and the technology displays diffusion potential – based on the tasks it can affect – across diverse sectors that typically account for a considerable share of activities.

Regarding continuous improvement over time, generative AI has benefited from improvements in compute and model capabilities since its inception that point towards a rapidly evolving technology. Ever more capable models are continuously being released, with the most recent ones excelling at various tasks regarding literacy, numeracy and logical reasoning, often even outperforming humans. Additionally, developments in the technology, such as AI agents, are broadening its potential by creating new use cases for the technology.

Considering innovation spawning, the analysis highlights that generative AI patents are relevantly cited by follow-on innovation in a broad number of application areas. Although these notably include, to a large extent, computer technologies and IT methods, they also considerably go beyond those, with applications ranging from medical technologies to logistics. The evidence also uncovers relevant positive feedback loops from follow-on innovation back to generative AI innovation, which suggest the likely relevance of generative AI as invention of a method of invention (IMI). Furthermore, generative AI is changing processes related to research and innovation – likely improving their productivity – and, at the same time, affecting several applied fields, notably including drug discovery and education.

Similarly to earlier GPTs, generative AI may exhibit a productivity paradox, as productivity gains may not materialise immediately and may be dependent on workers' skill development, the implementation of organisational changes and other complementary investments or innovations. Nonetheless, given the abovementioned time lags and the role of innovational complementarities, the evolution of earlier GPTs seems to provide encouraging signs that generative AI could lead to substantial improvements in productivity in the future, notably through the innovation-spawning channel.

The full realisation of generative AI's productivity potential in the long-term depends however on the implementation of a mix of policies aimed at fostering its widespread diffusion and trustworthy use across firms and sectors, supporting its continuous improvements over time, and encouraging its ability to spawn innovations in application sectors. The three defining characteristics of GPTs appear in fact particularly relevant from a policy perspective, highlighting the relevance of policy levers that not only foster technological adoption and diffusion, but also enable the effective use of generative AI and its applications across sectors alongside relevant organisational changes, and support innovation at the frontier. As the technology advances, ensuring that generative AI's use remains innovative and trustworthy and respects human rights and democratic values, in line with the OECD AI principles, will remain equally critical. These efforts will be instrumental in unlocking generative AI's full transformative potential as a GPT to drive innovation, enhance productivity, and achieve meaningful societal advancements.

1 Introduction

The release of the generative artificial intelligence (generative AI) chatbot ChatGPT in 2022 marked a new era in AI, highlighting unprecedented technological advances and mainstreaming some of the growing potential of generative AI. With the subsequent releases of competitors' chatbots and further improvements in Large Language Models (LLMs), generative AI appears to resemble humans unlike any other previous technological advances and, as such, interacts with humans in unprecedented ways.

Generative AI indeed represents a critical evolution in the field of AI, building on established systems and methods of earlier AI applications and extending their capabilities in new directions. Other pre-generative AI systems, such as certain machine learning applications, were primarily focussed on processing or classifying data and providing outputs based on patterns found from data (OECD, 2024[1]).

Generative AI systems build on these applications and extend their capabilities by producing novel content in response to prompts, based on patterns derived from data in a training phase. The generated contents are often hard to distinguish from human-created content, and may be in the form of text, image, audio, video, or multi-model formats. Users may also engage with products iteratively using natural language so that the technology produces outputs that are more contextually relevant based on defined parameters.

As businesses and governments focus their efforts on these developments, and the related governance issues, discussions have emerged about generative AI's potentially transformative effects, including with respect to automation, job replacement, and other societal risks such as impacts on worker rights and democracy, and even existential threats (OECD, 2024[2]). However, whether these changes will truly be transformational and whether the technology will bring significant benefits in the form of widespread productivity increases and substantially higher living standards and well-being remains a critical question in the economic and policy debate.

Historically, transformational technological innovations like the steam engine, electricity, and computers had profound impacts due to their general-purpose nature, permeating various economic processes and contributing to widespread productivity growth (Bresnahan and Trajtenberg, 1995[3]; Bresnahan, 2010[4]). While previous studies have attempted to evaluate the aggregate productivity effects of AI more broadly (Acemoglu, 2024[5]; Filippucci, Gal and Schief, 2024[6]; Briggs and Kodnani, 2023[7]; Aghion and Bunel, 2024[8]), this paper specifically focuses on analysing key characteristics of *generative* AI that are critical for its broader economic and social implications: those related to its general-purpose nature. The focus on generative AI is due to the technology's novel capabilities and rapidly expanding usage and range of applications, distinguishing it from other AI technologies. However, this does not preclude the possibility that other AI technologies could also exhibit traits of GPTs of their own.

After briefly discussing the current state of the technology and its potential, this study focuses on early empirical evidence aimed at assessing whether generative AI could be considered a GPT. First, the paper discusses key defining features of GPTs, of AI more broadly, and of generative AI. Subsequently, using qualitative indicators based on the theoretical literature and relevant use cases, as well as quantitative indicators based on early empirical evidence, including novel descriptive analysis, generative AI is evaluated through the lens of a GPT's defining characteristics of i) pervasiveness, ii) continuous improvement over time, and iii) innovation spawning. Attaining these three defining GPT characteristics in combination is essential in enabling a considerable economic impact of the technology, as generative AI's potential critically depends on the extent to which the technology can achieve widespread use that also generates substantial spillover effects and fosters innovational complementarities, raising overall productivity and driving economic growth.

Given the transformative potential of generative AI as a general-purpose technology, this study highlights the need for policy measures promoting the diffusion and effective use of trustworthy generative AI across firms and industries, supporting continuous improvements of generative AI, and encouraging follow-on innovation in sectors leveraging generative AI. The three defining characteristics of GPTs appear particularly relevant from a policy perspective, highlighting the relevance of policy levers that not only foster technological adoption and diffusion, but also enable the effective use of generative AI and its applications across sectors alongside relevant organisational changes, and support innovation at the frontier. Policymakers should therefore support investments in skills development and enable organisational changes to realise productivity gains, fostering the widespread diffusion and effective use of trustworthy generative AI. Additionally, continuous improvement and innovation across sectors should be encouraged, embedding guiding values, alongside broader risk-mitigation measures such as regulation and ethics frameworks. Relevant policy measures in this context include facilitating public and private investment in R&D, supporting research, innovation, and the transition from R&D to deployment, while promoting international cooperation and fostering an inclusive ecosystem and policy environment. By addressing these complementary areas, policymakers can help generative AI drive substantial productivity improvements while contributing to sustainable economic growth and societal well-being.

2 General-purpose technologies

Characteristics of GPTs

In order to understand whether generative AI could qualify as a GPT, it is worth examining the aspects that have defined GPTs in the past. Generally, inherent to GPTs is their transformative nature, including a wide range of applications, and their economic impact on an aggregate scale (Jovanovic and Rousseau, 2005[9]). More specifically, Jovanovic and Rousseau (2005[9]), based on Bresnahan and Trajtenberg (1995[3]), identify three features that characterise GPTs:

1. *Pervasiveness*: the GPT exhibits widespread diffusion across sectors.
2. *Continuous improvement* over time: the GPT becomes better as time progresses.
3. *Innovation spawning*: the GPT results in innovation in products and processes.

Similarly, Lipsey, Carlaw and Bekar (2005[10]) define a GPT as a single generic technology with an eventual widespread use that comes with substantial spillover effects. A GPT, therefore, not only experiences widespread diffusion (point 1), but the combination of points 2 and 3, that is, technological improvements over time and innovation in new applications, also defines GPTs by their “innovational complementarities”, a key element of how the emergence of a new GPT can raise overall productivity and thereby drive aggregate growth (Bresnahan, 2010[4]). Theoretical treatises of GPTs generally echo these defining features. Additionally, Gordon (2005[11]) emphasises the transformational impacts of GPTs not only on production and business, but also on household life. Common examples for previous or existing GPTs are the steam engine, electricity and more recently Information and Communication Technology (ICT) (Jovanovic and Rousseau, 2005[9]; Basu and Fernald, 2007[12]; Lipsey, Carlaw and Bekar, 2005[10]).

In light of the transformative effects on economies and societies originating from the spread of the steam engine, known as the “Industrial Revolution”, several GPTs that followed have been associated with this term. Given this context, it has been argued that AI, along with connected advanced digital technologies, could become the driving force behind a “Fourth Industrial Revolution”, with similar transformative impacts (Schwab, 2017[13]; Crafts, 2021[14]; OECD, 2017[15]). Indeed, previous GPTs such as the steam engine and electricity grew to widespread use throughout the economy, became significantly better over time by improved usability and resulted in an increasing number of applications in different application sectors. For more examples of GPTs in the literature, see Box 2.1.

Nonetheless, it is rarely straightforward to distinguish a GPT from other technologies using the three aforementioned criteria. While many technologies display certain characteristics of a GPT as enabling technologies (i.e. those that support new innovations), they often do not achieve the transformative impact associated with GPTs (Teece, 2018[16]). In this context, “true GPTs” are differentiated from other enabling technologies by their scale across all three dimensions (Bojovic, 2022[17]).

Additionally, it is sometimes unclear what exactly constitutes the technology in question, as GPTs evolve over long time horizons and give rise to new innovations. Here, the question arises whether specific components or technologies are driving the transformational processes and how related technologies relate to complementary capital (Field, 2008[18]). The case of ICT, for instance, saw rapid advances in both computer hardware and software as well as the development of the internet, which itself combines a complex interplay of technologies. As a result, analyses of past GPTs identified different technological drivers, such as, in the case of ICT, semiconductors (Bresnahan and Trajtenberg, 1995[3]), microprocessors (Bresnahan and Greenstein, 1999[19]) or wider ICT capital (Basu and Fernald, 2007[12]). This also ties in with the idea of technological paradigms and technological revolutions (Dosi, 1982[20]; Perez, 2009[21]), where a “set of interrelated radical breakthroughs” can lead to paradigmatic shifts. In particular, the idea of technological paradigms originally put forward by Dosi (1982[20]) posits that, similar to scientific paradigms, innovation tends to happen on a trajectory within an outlook regarding the relevant issues addressed by technological solutions. In this context, “extraordinary” technological breakthroughs can lead to a shift in the technological paradigm, and to relevant technological revolutions (Perez, 2009[21]).[1] Given that GPTs can be key drivers of these dynamics, it is worth considering whether paradigmatic shifts and technological revolutions are driven by the emergence of a cluster of technologies rather than a single technological breakthrough.

In this context, Bresnahan (2024[22]) highlights that when there is a technology stack where related complementary technologies exhibit GPT characteristics, it is key to consider whether the particular technology being evaluated as a GPT generates a positive feedback loop between the technology and its application sectors. This is important as the typical focus in GPT discussions tends to be on whether the particular GPT technology exhibits an improvement relative to other technologies in the stack, rather than considering whether a self-sustaining innovation cycle can be formed from the GPT technology to innovation development in its application sectors and back to improvements in the GPT itself. In the instance of pre-generative AI technologies, Bresnahan (2024[22]) observes that while they had early commercial applications in a narrow range of application sectors, they do not appear to achieve a positive feedback loop.

In this context, this study’s focus on generative AI as a GPT, including whether it generates a positive feedback loop with its application sectors, does not preclude the possibility that other AI technologies could also exhibit traits of GPTs of their own, and may relevantly further inform the broader debate on whether AI can be considered a GPT after the advent of generative AI.

Box 2.1. Examples of historical GPTs

Identifying GPTs is both a conceptual and empirical challenge. As a result, although various technologies have been labelled as GPTs in the literature, there is no universally agreed-upon set of GPTs. Some earlier inventions, such as the steam engine and electricity, are frequently brought up in the literature, while others, especially those that emerged since the onset of the information age, differ in the breadth and specificity of the definitions in the studies. The interpretation of whether a GPT represents a specific invention or a set of interrelated technologies can differ (Bekar, Carlaw and Lipsey, 2017[23]). In the context of the ICT revolution, for instance, the GPTs identified range from ICT as a whole to more specific technologies such as semiconductors. Additionally, technologies may differ in their application of the concept of IMI. Some technologies may be considered GPTs but not IMIs by certain authors, or vice versa, or the concept of IMI may not be applied at all. There is extensive literature assessing the role of ICT in productivity growth, often from the GPT perspective. The list below provides a non-comprehensive overview over GPTs discussed in the literature.

- Steam engine (Lipsey, Carlaw and Bekar, 2005[10]; Bresnahan, 2010[4]; Rosenberg and Trajtenberg, 2004[24]; Crafts, 2004[25])
- Electricity (Lipsey, Carlaw and Bekar, 2005[10]; David, 1990[26]; Bresnahan, 2010[4]; Jovanovic and Rousseau, 2005[9]; Moser and Nicholas, 2004[27]; Ristuccia and Solomou, 2014[28])
- Railroads (Lipsey, Carlaw and Bekar, 2005[10])
- Factory system (Lipsey, Carlaw and Bekar, 2005[10])
- Information and communication technology (ICT) (Lipsey, Carlaw and Bekar, 2005[10]; Liao et al., 2016[29]; Basu et al., 2003[30]; Basu and Fernald, 2007[12]; Cardona, Kretschmer and Strobel, 2013[31]; Jovanovic and Rousseau, 2005[9])
- Computer (David, 1990[26])
- Semiconductors/microelectronics (Bresnahan and Trajtenberg, 1995[3])
- Internet (Agrawal, Gans and Goldfarb, 2023[32]; Naughton, 2016[33]; Clarke, Qiang and Xu, 2015[34])
- Artificial intelligence (AI) (Agrawal, Gans and Goldfarb, 2023[32]; Cockburn, Henderson and Stern, 2019[35]; Brynjolfsson, Rock and Syverson, 2019[36]; Crafts, 2021[14]; Klinger, Mateos-Garcia and Stathoulopoulos, 2018[37])
- Three-masted sailing ship and printing press (Bekar, Carlaw and Lipsey, 2017[23])
- Chemical engineering (Rosenberg, 1998[38])
- Nanotechnology (Youtie, Iacopetta and Graham, 2007[39]; Shea, Grinde and Elmslie, 2011[40])
- Blockchain (Kane, 2017[41]; Filippova, 2019[42]; Catalini and Gans, 2020[43])

GPTs and implications for productivity

The nature of GPTs allows them to create innovational complementarities, which generate vertical innovation externalities between the GPT and its application sectors, as well as horizontal innovation externalities across application sectors (Bresnahan and Trajtenberg, 1995[3]; Bresnahan, 2010[4]). This generates a positive innovation loop which contributes to driving economic growth and aggregate productivity. As such, the inception of a GPT is “consequential” and its transformative potential distinguishes it from other technologies (Field, 2008[18]).

Yet the "Modern Productivity Paradox" (Solow, 1987[44]) highlights a puzzling trend: many advanced and emerging economies experienced slow productivity growth towards the second half of the 20th century despite rapid technological advancements and the emergence of new GPTs such as ICT in the same period (David, 1991[45]; Brynjolfsson, 1993[46]). This could partly be explained by the fact that diffusion or effective technological use has been slow and unequal among firms, with firms lagging behind the global technology frontier potentially unable to reap the productivity benefits of digital technologies (Andrews, Criscuolo and Gal, 2016[47]).

Nonetheless, recent research by Brynjolfsson, Rock and Syverson (2021[48]) suggests that the productivity paradox could be related to a delay in realisation of returns of new GPTs. The authors coin the phenomenon "Productivity J-curve", where initial productivity growth of new GPTs is underestimated as unmeasured intangible capital stocks are accumulated, and productivity growth is later overestimated as capital service flows yield measurable output. Similarly, growth accounting estimates show that while GPTs have yielded productivity benefits, these were often realised with large delays and alongside other transformational changes to the economy (Crafts, 2021[14]). Indeed, the productivity impact of ICTs has materialised over time, providing a potential resolution to the productivity paradox (Cardona, Kretschmer and Strobel, 2013[31]). In particular, ICT growth since the 1990s contributed to TFP accelerations (Basu and Fernald, 2007[12]) and labour productivity growth (Byrne, Oliner and Sichel, 2013[49]) in the 2000s in the United States. Similar analyses show consistent results also in other OECD Member countries (Colecchia and Schreyer, 2002[50]; Pilat and Lee, 2001[51]; Ceccobelli, Gitto and Mancuso, 2012[52]; Banday and Erdem, 2024[53]; Cette, Nevoux and Py, 2021[54]).[2]

To understand the channels through which new GPTs affect productivity growth, it is important to consider their interplay with an "invention of a method of invention" (IMI) (Crafts, 2021[14]; Cockburn, Henderson and Stern, 2019[35]). GPTs, which raise the productivity of the production of goods and services, are distinct from IMIs, which raise the productivity of the production of ideas, and a GPT may or may not be an IMI. A subset of GPTs also provide IMIs, which bring about cost reductions in innovation efforts and qualitatively improve how research is conducted and how new inventions enter the economy's knowledge stock. For example, while the steam engine and ICT are generally considered GPTs, only the latter provides an IMI (Crafts, 2021[14]). More recently, deep learning technologies may provide an IMI as they enable a new approach to scientific and technical research (Cockburn, Henderson and Stern, 2019[35]). For GPTs and IMIs that coincide, such as ICT, Crafts (2021[14]) suggests that the contribution to productivity growth as an IMI would not be attributed to the GPT by growth accounting but would materialise as other TFP growth in the aggregate economy. Additionally, many societal benefits brought about by the IMI would arguably remain largely unaccounted for in productivity measures, such as health benefits from improved pharmaceutical research.

Recent literature identifying new GPTs

Recent literature has attempted to classify GPTs – beyond a specific focus on generative AI – using different empirical approaches. In particular, Petralia (2020[55]) develops a three-dimensional indicator to identify GPT characteristics using patent data and evaluates the methodology against electric & electronic and computer & communications technologies. Specifically, patenting growth rates are used to measure technologies' scope for improvement, a text mining algorithm on technology-specific vocabulary in patent documents is used to identify the range of technologies' uses, and the co-occurrence of technological claims in patents is used to measure complementarity with other technologies.

Still leveraging patent data, a recent stream of literature further analysed the GPT nature of pre-generative AI applications. Hötte et al. (2022[56]) use patent data to study whether AI patents exhibit intrinsic growth, generality and innovation complementarities. However, the authors find that the result is sensitive to the classification approach for AI patents (i.e. keyword, science-citations, WIPO, USPTO approaches), with a lack of overlap and heterogeneity across the approaches. Calvino et al. (2023[57]) study AI-related patents in the United States and find that "core" AI patents are more original and general,[3] and tend to spur AI-related innovation beyond their own respective field. Relatedly, Biggi et al. (2025[58]) investigate whether AI acts as a GPT in the context of driving green innovation, and find that "green intelligence" (green inventions that rely on AI technologies), too, exhibits greater originality and generality than AI and green technologies each but not a higher market value. Damioli et al. (2025[59]) find that AI patenting exhibits pervasiveness beyond the ICT technological paradigm that has affected existing technological hierarchies and accelerated further innovations. Finally, Santarelli, Staccioli and Vivarelli (2022[60]) study US AI patenting and find evidence of AI technologies' increasing pervasiveness across industries and supporting innovation, suggesting the emergence of a technological paradigm shift.

Focusing on the innovation spawning GPT characteristic of AI, Grashof and Kopka (2022[61]) find that ownership of patents on AI applications has a positive influence on the firm's subsequent radical innovations (proxied by patents with new technology combinations), while ownership of patents on AI techniques has a negative influence. At the same time, there are heterogeneous impacts across firms, with larger firms benefiting from AI applications, while SMEs gain from AI techniques.

Apart from this stream of literature based on patent data, Goldfarb, Taska and Teodoridis (2023[62]) use job-posting data (which indicate labour demand for technology-specific skills) to identify GPTs based on whether they appear prominently across job postings in different sectors, evaluating their innovation potential using the number of job ads that require the technology skill as a proxy, and related innovation in application sectors. They find that a cluster of technologies comprised of machine learning and related data science technologies are likely to be GPTs.

Some of the abovementioned studies provide a relative ranking of technologies according to their likelihood of being a GPT, given the difficulty of a definitive threshold regarding which technology can be considered a GPT, based on quantitative indicators. This is valuable given Field's (2008[18]) critique that many technologies have been inconsistently labelled as GPTs, rendering the concept less useful as true "engines of growth," especially given the short time frames and continuous technological improvements.

Finally, recent literature has also assessed the characteristics of AI users and the diffusion patterns of AI more broadly, relevant dimensions for the extent to which it can qualify as a GPT (Trajtenberg, 2018[63]). Filippucci et al. (2024[64]) highlight that while some AI technologies can self-improve and spur innovation by boosting research, the adoption of AI technologies is more limited as compared to other GPTs. On average across OECD Member countries, adoption rates of AI among firms are as low as 8% as of 2023 (OECD, 2024[65]), and still tend to be concentrated among large firms and in the ICT and professional services sectors (Calvino and Fontanelli, 2023[66]). Similarly, McElheran et al. (2024[67]) find that fewer than 6% of firms in the United States adopted AI-related technologies such as machine learning, machine vision, natural language processing (NLP) and voice recognition in 2018, while Humlum and Meyer (2020[68]) find similarly low rates of AI adoption among firms in Denmark in 2017.

3 Generative AI

This section outlines the unique characteristics of generative AI compared to other AI technologies to evaluate the extent to which the former has the potential to be considered as a new GPT.

Generative AI vs other AI technologies

Generative AI technologies emerged in the economy for wider use in 2022, building on earlier AI applications, which leverage deep neural networks by finding patterns from training data that are then used to process previously unseen data (OECD, 2024[1]). Unlike pre-generative AI technologies that analyse data to make predictions and classifications, generative AI can create novel content (including text, images, audio and videos) and insights that are often indistinguishable from human-created content, based on patterns and structures learnt from training data (Banh and Strobel, 2023[69]; AWS, 2024[70]; OECD, 2023[71]; Lorenz, Perset and Berryhill, 2023[72]).[4] It is also easier for users without technical knowledge to engage with generative AI products using its unique "prompting" feature, which allows the use of natural language to interact with products. In this sense, the very nature of generative AI technologies and their scope of applicability, notably including the generation of text, makes them different from other AI systems. In addition, generative AI technologies leverage extremely large datasets and can focus on creating new and diverse content, rather than identifying boundaries of existing data to produce an algorithm (Banh and Strobel, 2023[73]).

While recent literature has to some extent focussed on whether AI qualifies as a GPT, mainly based on evidence related to pre-generative AI systems, and whether AI has the potential to rejuvenate growth under a "Fourth Industrial Revolution" (Schwab, 2017[13]), few scholars have comprehensively explored whether *generative* AI can qualify a new GPT. Assessing this more directly can also and relevantly further inform the broader debate on whether AI can be considered a GPT after the advent of generative AI.

A first seminal study assessing the potential of generative AI as a GPT has been carried out by Eloundou et al. (2024[74]). Their analysis aims at characterising LLMs through their labour market impact, considering the breadth of exposure to LLM-powered software across occupations and by analysing productivity gains in the labour market. With 80% of the US workforce having at least 10% of their work tasks affected by LLMs, they find a large potential exposure of workers to generative AI, providing early empirical evidence of the technology's *pervasiveness* in the economy, one of the characteristics of GPTs discussed above.

Going beyond pervasiveness, given that generative AI has been shifting AI tasks from data-driven and discriminative tasks to sophisticated and creative ones (Banh and Strobel, 2023[73]), the innovative breakthrough potential achievable by generative AI could distinguish it from other technologies and solidify it as a new GPT. Indeed, Bresnahan (2024[22]) observes unique characteristics of generative AI that could lead to the technology spawning innovations across many application sectors, in turn generating a positive feedback loop. First, generative AI foundation models are trained on large data that scale with performance[5] and can be adapted to applications with lower cost and effort. There are lower integration costs and fewer complementary investments needed for an organisation to adopt the technology (Brown et al., 2020[75]). This allows for a faster diffusion of the technology across firms with varying absorptive capacities, as well as a wider adoption across various sectors as compared to traditional AI technologies. This also supports the development of innovative applications across sectors.

Second, unlike earlier AI technologies that required modular applications and automated processes, generative AI models can be applied to a wide range of tasks with minimal fine-tuning or context-specific training (Brown et al., 2020[75]). There are improved human-machine interaction as generative AI foundation models can work well even with informal or incomplete direction. This flexibility and ease of development supports diverse applications across various sectors, even those outside of digital-intensive industries or internet giants (Bresnahan, 2024[22]).

Furthermore, while AI technologies were initially framed as an “automation” technology, there appears to be a shift towards framing recent technological developments, including generative AI technologies, as an “augmentation” technology (Bresnahan, 2024[22]).[6] This is useful when considering that innovations in application sectors could involve the emergence of new organisational structures, new relationships with customers, and other tasks. These changes would take time to develop but are likely to make further progress in launching a positive feedback loop as compared to creating “automation” applications for the technology.

Moving away from firms, some generative AI applications have “off-the-shelf” characteristics unlike pre-generative AI technologies, which allows them to be applied in everyday life for households, not just for firms. This aspect resonates with the criterion put forward by Gordon (2005[11]) that characterises GPTs as transformative for household life.

Due to generative AI’s distinct characteristics, this paper examines generative AI as a distinct technology from the broader pool of pre-generative AI systems.

Box 3.1. Examples of generative AI products

Generative AI can create novel content and insights that are often indistinguishable from human-created content, based on patterns and structures learnt from training data. A wide range of applications and products that leverage this technology to provide personalised content for users have been created (Gozalo-Brizuel and Garrido-Merchán, 2023[76]). Examples of text, image, video and audio generative AI applications are listed below.

Text:

- General applications with text generation, common-sense, spatial and mathematical reasoning capabilities: OpenAI ChatGPT, Google Bard/ Google Minerva, Microsoft Copilot, Anthropic Claude (Marr, 2024[77])
- Healthcare applications providing medical information and advice: Chatdoctor, Glass Health, Google's Med-PaLM 2
- Tourism travel planners providing customised travel itinerary, accommodation and transport recommendations: Roam Around, Kayak Plug-in for ChatGPT
- Coding assistants that help developers create programmes efficiently: AlphaCode, GitHub Copilot (Turing, 2024[78])
- Coding assistants that create websites and applications through text prompts: Durable, FlutterFlow
- Coding assistants that create production-ready code from designs: Locofy

Image:

- Text-to-image applications: DALL-E 2, Midjourney, OpenART, Bing AI Image Creator
- Image editing applications: Photoroom AI

Video and audio:

- Text-to-video applications: Synthesia, Kaiber, Opus AI
- Image-to-video applications: GeoGPT

4 Generative AI as a GPT

The following section provides a discussion of whether generative AI could qualify as a GPT along the three dimensions discussed above of i) pervasiveness, ii) continuous improvement over time and iii) innovation spawning, drawing insights from both the nascent literature as well as presenting some indicative trends from various data sources.

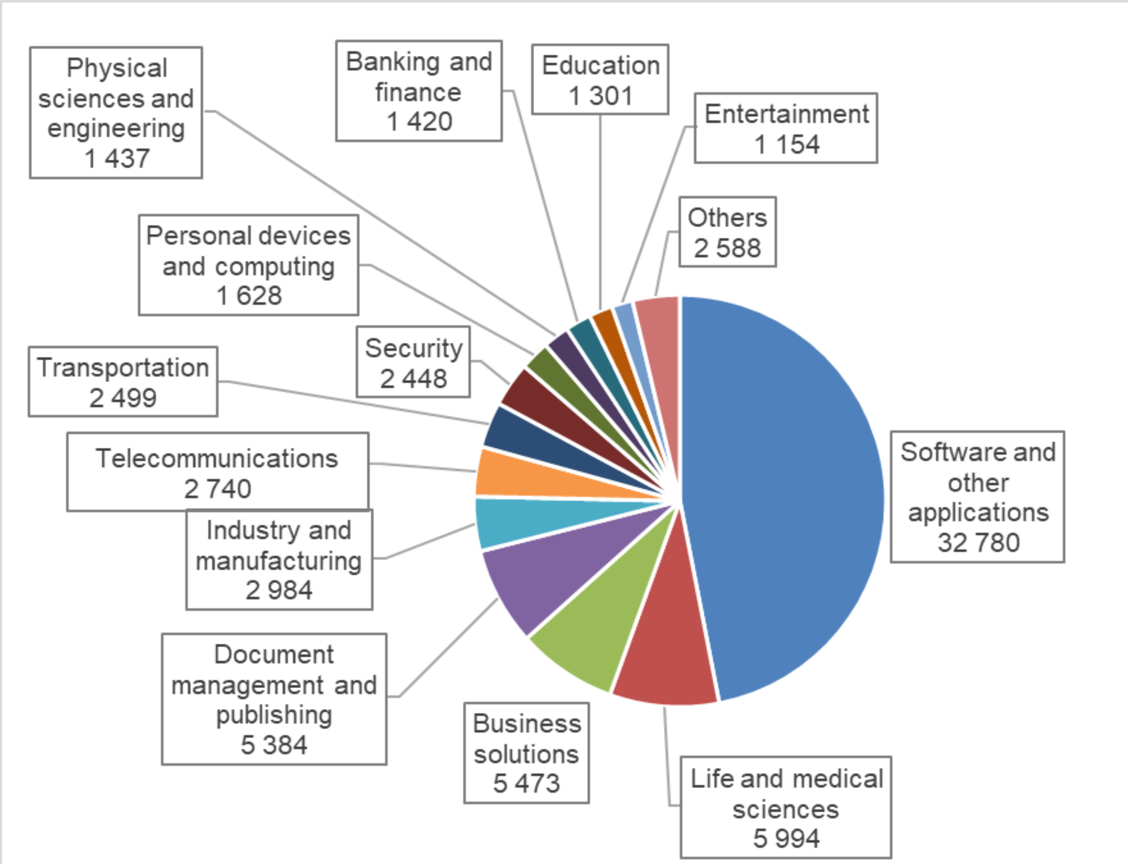
Pervasiveness

As previously discussed, *pervasiveness* is a key feature of GPTs, pointing to the extent to which the technology exhibits widespread diffusion across the economy. This subsection will discuss key qualitative and quantitative indicators that appear informative in assessing the pervasiveness of generative AI, despite its initial phase of diffusion. First, it focuses on the heterogeneity in the technology's application areas, based on quantitative indicators of technological developments proxied with patent data, as well as further elaborating about some key use cases. Second, it highlights key insights from official statistics, as well as from recent individual surveys, discussing the most recent figures of the actual rates of generative AI use across the economy, its sectors, or across the workforce. Third, considering generative AI's links with automation or augmentation of labour, as well as the fact that technology diffusion is a gradual process, pervasiveness is further assessed taking a longer-term perspective and focusing on the extent to which generative AI has the potential to affect occupations, and in turn sectors of economic activity based on their occupational composition, building upon the recent literature analysing tasks' exposure to generative AI.

Application areas

Generative AI technologies have been incorporated in products, services and processes across many application areas and industries.[7] Analysing recent patent data provides a first assessment about the heterogeneity in the technology's application areas.[8] Focusing on generative AI patents filed globally from 2000 to 2023, Figure 4.1 shows that generative AI spans a wide range of over twenty-one application areas. While 'Software' accounts for the largest share of generative AI patents,[9] a number of other application areas relevantly emerge. Notably, key application areas for the technology beyond 'software' include 'life and medical sciences', 'business solutions', 'document management and publishing', and 'industry and manufacturing'. While the technology is still evolving and producing innovations that may not be filed in the form of patents, or may not yet be visible in the data under scrutiny, this analysis provides some early evidence that generative AI has widespread applicability and may be integrated across several application areas.

Figure 4.1. Total number of generative AI patents published globally by application area, 2000–23



Note: 9 application areas with less than 1 000 patents are grouped together under 'others' and these include: 'arts and humanities', 'computing in government', 'networks and smart city', 'industrial property, law, social and behavioural sciences', 'cartography', 'military', 'energy management', 'agriculture'. Patents that cannot be assigned to a specific application based on the patent abstract, claims or title are included in the category 'software and other applications'.
Source: Authors' calculations based on WIPO data on generative AI patents, https://doi.org/10.34667/tind.49740.

Beyond patented applications of generative AI, the technology is utilised by key sectors of the economy to carry out tasks or activities, and several examples are reported below (though this list is not intended to be exhaustive). Sectors utilising generative AI include manufacturing, healthcare, business services, finance, education and art (WIPO, 2024[79]; Ooi et al., 2023[80]; André et al., 2025[81]). This highlights some examples of relevant use cases, providing initial evidence about its diffusion, before turning to analyse its actual and potential use.

- *Manufacturing*: Generative AI is used to optimise the design and development of products and production processes. Digital twin programming and synthetic data generation also allow for simulation and testing to prepare for disruptions and improve processes. Use cases have further been documented for workforce and skill optimisation, quality control, predictive maintenance, demand forecasting, and marketing strategy (Doanh et al., 2023[82]).
- *Healthcare*: Generative AI can be used to augment medical diagnosis and treatment (e.g. by helping patients provide a more complete description of symptoms to healthcare professionals and providing tailored patient diagnosis and treatment recommendation). It can also aid drug discovery and development by screening and designing molecules.
- *Business services*: Generative AI can be used to enhance the customer user experience through answering customer queries or providing personalised product purchase recommendations and

assistance. By producing creative ideas and enabling customer co-creation, generative AI has also improved marketing strategies.

- *Finance*: Generative AI is used by commercial and retail banks to improve customer engagement and develop tailored financial advice and investment strategies. Due to the high regulated nature of finance, the technology has been deployed relatively slowly by financial market participants (OECD, 2023[83]). Nonetheless, the technology could be used as a starting point to simplify a firm's data analysis and reporting. In the field of financial market prediction, the technology is able to simulate complex financial market data under various scenarios, which is useful for understanding market shifts and stress-testing investment strategies (Che et al., 2024[84]).
- *Education*: Generative AI is used to enhance the effectiveness and accessibility of learning for students by providing easily accessible and understandable information, tailored responses to questions and personalised feedback and assistance.
- *Art*: Generative AI may be integrated in creative design processes for various art forms such as visual art, music, literature, video and gaming, at different various stages of the creation process (e.g. training data selection, crafting prompts, using AI-generated products for downstream creative applications) (Epstein et al., 2023[85]).

Current adoption rates

Beyond exploring applications and use cases, a primary way to assess a technology's pervasiveness is by examining its diffusion across the economy, assessing the extent to which it is adopted by sectors, firms, and workers. At the aggregate level, as discussed in the previous section, official statistics show that while the use by firms of AI technologies in general has remained relatively low, at 8% across OECD Member countries in 2023 (OECD, 2024[65]), and concentrated among larger firms, it has been increasing recently. In the European Union (EU), overall adoption by enterprises rose to 13.5% in 2024, from 8% in 2023 (Eurostat, 2025[86]). At the sector level, the current spread of AI appears to be predominantly driven by the information and communication technology sector (28% across OECD Member countries in 2023), while adoption in other sectors such as manufacturing (8%) and construction (4%) lags behind. Similarly, recent US Business Trends and Outlook Survey estimates show that AI adoption rose from 3.7% in September 2023 to 5.4% in February 2024, and sectors that rely heavily on cognitive tasks (e.g. 'information', 'education', and 'professional, scientific, and technical services') adopt AI at higher rates (Bonney et al., 2024[87]).[10]

For generative AI, comprehensive data on firm usage of the technology use have been emerging only very recently and data challenges remain. Challenges to collecting comparable and up-to-date data on generative AI include a time lag in the publication of official statistics, heterogeneous definitions across statistical offices, and a possible under-reporting of firm usage as generative AI may be embedded in products or services that may not be explicitly recognised at the firm level even when it is utilised at the worker level. In the EU, official statistics show that 5.4% of enterprises used AI technologies related to natural language generation in 2024, though this is only one aspect of generative AI technologies and does not provide the full picture of firm usage (Eurostat, 2025[86]). In Canada, approximately 9.3% of businesses used generative AI in the first quarter of 2024, while 4.6% had plans to use it (Statistics Canada, 2024[88]).These official figures provide only a glimpse into the state of overall AI and generative AI adoption and there may be under-reporting given the challenges highlighted earlier. However, the recent increase in AI adoption aligns with the introduction of generative AI to the market, suggesting that generative AI may significantly contribute to overall AI adoption.

In line with the consideration put forward by Gordon (2005[11]) to assess pervasiveness for GPTs, it is relevant to examine generative AI's diffusion beyond the firm and industry level, but also at the individual and household levels. Indeed, individuals and workers have been rapidly adopting this technology to generate new data and insights. ChatGPT, a chatbot based on Large Language Models (LLMs) that generates text in response to human prompts, became the fastest-growing consumer application in history after it was launched in November 2022, and had more than 200 million weekly active users as of August 2024 (Reuters, 2024[89]). A large-scale survey conducted in late 2023 finds that more than half of the workers in Denmark have adopted ChatGPT (Humlum and Vestergaard, 2024[90]). In the United States, survey estimates show that about 40% of the population aged 18-64 use generative AI as of late 2024, while more than 22% of workers use it at least once in the last week for work (Bick, Blandin and Deming, 2024[91])). Furthermore, younger, more educated, and higher-wage workers seem to adopt generative AI at a faster rate. Notably, the authors find that overall adoption of generative AI is faster than previous GPTs such as PCs and the internet. They argue that ease of accessibility, limited end-user cost and user-friendly features of generative AI tools have driven rapid adoption among individuals.

Furthermore, recent analysis based on internet traffic data (from January 2022 to March 2024) highlights that, as of March 2024, the top generative AI tools attract about 3 billion monthly visits, from hundreds of millions of users (Liu and Wang, 2024[92]). Countries with higher income levels, higher youth population share, better digital infrastructure, stronger human capital, specialisation in high-skill tradable services, and English proficiency generally have higher generative AI usage (Liu and Wang, 2024[92]). Nonetheless, middle-income countries have a disproportionately high adoption of generative AI relative to what is implied by their income levels alone, contributing over 50% of global traffic, highlighting the strong adoption and integration of generative AI in economies with growing digital maturity. This also implies a pervasiveness of the technology beyond just a group of countries that are technology leaders.

The evidence discussed above highlights that, while adoption rates among firms are typically lower than adoption rates among individuals, both still appear to be growing. One explanation to reconcile the difference in generative AI usage between firms and individuals may be related to the fact that AI adoption appears concentrated among large firms, which by definition employ more workers, often with higher skills.

Diffusion potential

Given the early stages of the technology, and its growing adoption, it appears important to consider its future diffusion potential. In fact, the potential for generative AI to find rapid and widespread adoption across sectors of the economy may also depend on generative AI's links with automation or augmentation of labour, how sectors use labour and capital, as well as how task profiles of sectors are affected by generative AI. A distinguishing feature of generative AI compared to other predictive AI applications or many past GPTs, is the way it is integrated into processes. Notably, generative AI interacts directly with workers, potentially making labour more productive (*labour augmentation*), and may also take over some tasks previously performed by workers (*labour automation*). This could explain the higher adoption rates or potential observed in some labour-intensive services industries as compared to capital-intensive industries such as manufacturing.

Moreover, a recent strand of literature has emphasised the importance of the task profile affected by the adoption of GPTs (Acemoglu and Restrepo, 2018[93]). The deployment of the GPT may reallocate tasks between labour and capital as certain tasks previously performed by human labour can be executed autonomously by capital.[11] In the case of generative AI, some more cognitive and creative tasks notably would see a reallocation from labour towards capital. At the same time, generative AI also creates new tasks for humans (e.g. prompt engineering), implying a reverse reallocation between factors in parallel. The heterogeneity in diffusion between sectors is therefore likely to depend on their respective task profiles. However, as the technology develops, the task profile impacted by the technology may evolve as well. For example, the use of generative AI in agentic AI,[12] AI systems making autonomous decisions, and the development of collaborative robots (cobots)[13] in the manufacturing sector may lead to a broader set of tasks in more sectors to be impacted by generative AI.

Relevantly, recent literature analysing task exposure to generative AI may provide an indication of the extent to which generative AI has the potential to affect occupations, a relevant dimension for the future pervasiveness of the technology. As previously discussed, Eloundou et al. (2024[74]) estimate that approximately 80% of the US workforce could have at least 10% of their work tasks affected by LLMs, and approximately 19% of workers could have at least 50% of their work tasks affected. In particular, occupations involving programming and writing skills have the highest exposure. In line with this, management, business, and computer occupations have higher usage rates of generative AI of more than 40% (Bick, Blandin and Deming, 2024[91]), and highly-educated, highly-paid, white-collar occupations are most exposed to generative AI (Felten, Raj and Seamans, 2023[94]). Nonetheless, recent work accounting for generative AI's potential to substitute or complement human labour shows that high-skill occupations with higher exposure also have higher potential for complementarity (Pizzinelli et al., 2023[95]). Consequently, workers in these occupations are less likely to experience adverse labour market outcomes. Meanwhile, other occupations that are highly exposed but have low complementarity, such as clerical support occupations, are at higher risk of substitution. At the same time, the skills demanded from occupations with higher exposure to generative AI may evolve over time, and skills such as management, business processes and social skills may become more sought after (Green, 2024[96]).

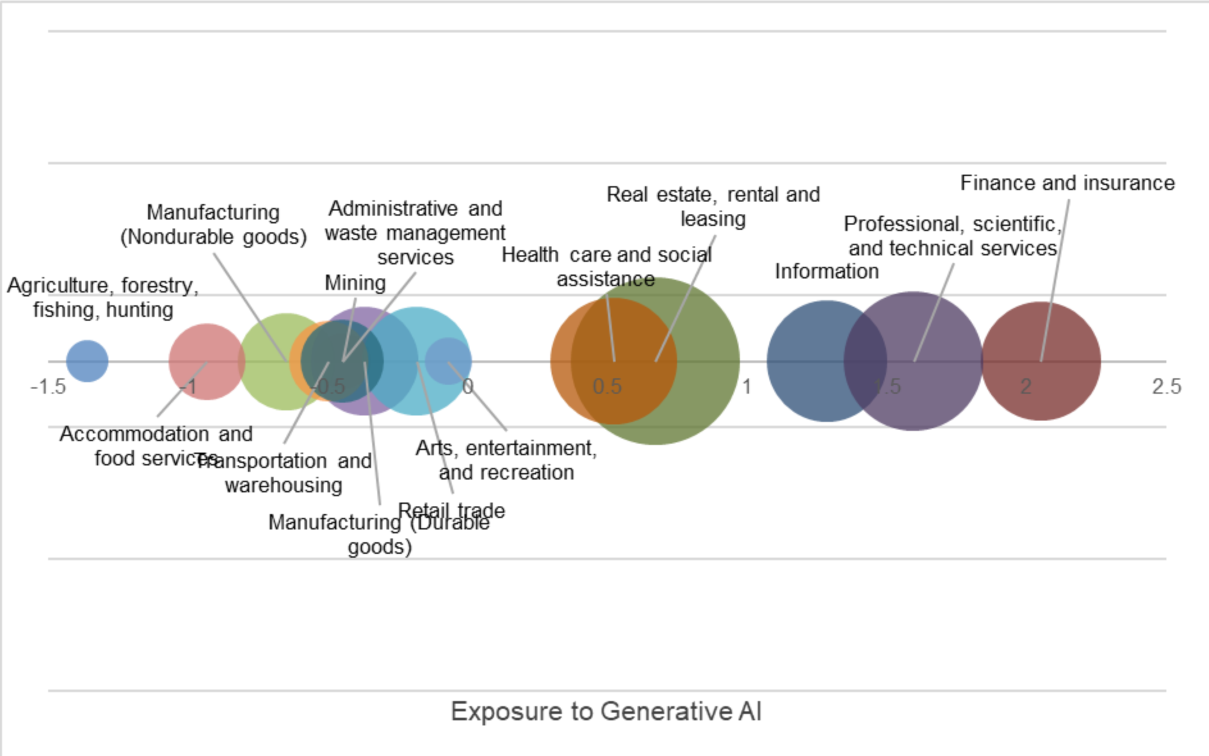
Nonetheless, a wide range of occupations use generative AI regularly at work, particularly for writing, interpreting, and administrative tasks. More recent analysis on generative AI conversations from December 2024 to January 2025 find that 36% of occupations use the technology for at least 25% of their tasks, suggesting that the technology has diffused into task portfolios across a substantial portion of the workforce (Handa et al., 2025[97]). Furthermore, most occupations use generative AI to both automate and augment tasks, suggesting that it can serve as both an efficiency tool and collaborative partner. These findings highlight the wide and rapid diffusion of generative AI technologies across occupations.

Occupational exposure to generative AI may also be used to analyse the extent to which generative AI has the potential to affect sectors based on their occupational task composition (Felten, Raj and Seamans, 2023[94]). In the US, the 'finance and insurance', 'professional, scientific and technical services', and 'information' sectors have higher exposure to generative AI based on their occupational task composition. These same sectors are identified as being highly affected by AI technologies more broadly using a multidimensional approach[14] (Calvino et al., 2024[98]). Specifically, business services such as 'media', 'telecommunications', 'IT services', 'legal and accounting', and 'finance and insurance' tend to exhibit higher levels of AI intensity across dimensions.

As sectors with higher exposure to generative AI are also more AI intensive, it may be easier for firms in these sectors to adopt the technology with fewer adjustment costs. Bresnahan (2024[99]) identifies three tiers of firms based on their adoption of AI: Tier 1 firms are already using algorithmic, predictive and scalable tools. These tools may also be modular, making it easy to replace the subsystem with more recent generative AI algorithms. These firms may adopt generative AI faster due to fewer or no organisational adjustment costs. Tier 2 firms, while using some predictive applications and tools, encounter higher adjustment costs than Tier 1 firms in adopting generative AI and may lack sufficient use cases to digitalise further. Finally, Tier 3 firms are not able to easily integrate generative AI into their operations or have yet to develop a plan for reorganising their business functions. Consequently, the adoption of the technology may be slower for Tier 2 and Tier 3 firms. For such firms to adopt generative AI in their operations, complex system-wide changes that promote that adoption of generative AI beyond the individual task-level may be needed (Agrawal, Gans and Goldfarb, 2021[100]).

Sectors exposed to generative AI tend to account for a considerable share of the economy. Figure 4.2 below shows this based on Felten, Raj and Seamans' (2023[94]) indicator for industry exposure to generative AI and real GDP by industries in the United States in 2023. Notably, US industries that are most exposed to generative AI also had a larger contribution to real GDP in 2023. This implies that despite sectoral heterogeneity in exposure, sectors that are most heavily exposed play a greater role in driving economic output. Additionally, these industries could be in a better position to make substantial investments to better utilise generative AI in their business models, including for instance in resource-intensive infrastructure (e.g. data centres) and computational resources. Larger industries are also more likely to have access to vast amounts of data for generative AI model training to improve or finetune model capabilities. This could in turn have implications for the speed of improvement of the technology, which is explored in the next subsection.

Figure 4.2. US industries by exposure to generative AI and real GDP in 2023



Note: The bubble size is proportional to Real GDP of the industry in 2023 ($US, billions). AI Industry Exposure (AIIE) data is a normalised scale. The most granular GDP by industry data is at the 3-digit NAICS level while the AI Industry Exposure (AIIE) data is at the 4-digit NAICS level. The average of component AIIE was used to derive AIIE estimates at the 3-digit NAICS level. To derive the indicator for exposure to generative AI for the 2-digit NAICS sectors in the US, the average of AIIE of the component 3-digit NAICS sectors was used.
Source: Authors' calculations based on GDP by industry data from US BEA, and AI Industry Exposure data from Felten, Raj and Seamans (2023[94]).

Continuous improvement over time

Next, a key feature of GPTs is their c*ontinuous improvement over time*. The emergence of generative AI is a result of the continued sophistication of earlier AI technologies. While the technological foundations of generative AI were laid in the 1950s with the emergence of the concept of machines mimicking human intelligence, the first machine learning algorithm and the first neural network, there have been significant advancements in neural networks, large datasets, and computational power since 2015 (OECD, 2023[71]). The emergence of the Transformer architecture in 2017 (Vaswani et al., 2017[101]) marked a key milestone, enabling large language models (LLMs) and driving improvements in natural language processing (NLP), but also in computer vision, and vision-language tasks (Cao et al., 2023[102]). This architecture, featuring positional encodings, attention mechanisms, and self-attention, allows for more efficient natural language processing. Model development has focussed on increasing parameter counts to capture complex patterns, while also striving for training efficiency to reduce environmental and financial costs. Additionally, there is a growing interest in multilingual models to support diverse languages, making AI more inclusive and accessible. These technological developments have driven rapid progress in AI systems, improving their performance and applicability across various sectors.

In this context, this subsection will analyse more closely advancements in generative AI's capabilities over time. First, it focuses on computational resources (compute), which refer to the hardware, software, and infrastructure needed to train and run generative AI systems, one of the main drivers of the increasing capabilities of generative AI models (Bengio et al., 2025[103]). Second, it examines the performance of generative AI models discussing a range of performance benchmarks and tests, assessing how the technology's capabilities have been evolving over time across various dimensions. Third, it discusses how the technology may potentially advance in the future based on recent developments.

Compute and training

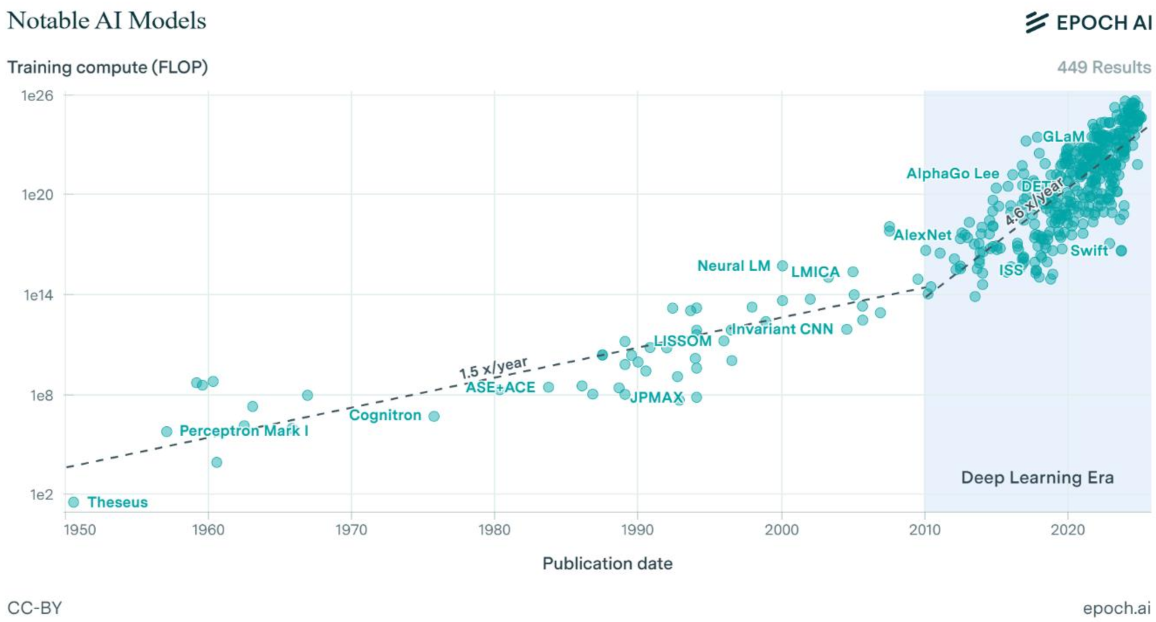
The essential components of training large AI models include datasets, computational resources and software in the form of algorithm architectures and deep learning frameworks (Tu et al., 2024[104]). These inputs play distinct roles in the development and deployment of AI models, varying by stage. In this context, several scholars have studied "scaling laws" of generative AI technologies, including LLMs, generative image and video modelling, and reinforcement learning (Wei et al., 2022[105]; Henighan et al., 2020[106]; Hilton, Tang and Schulman, 2023[107]; Hoffmann et al., 2022[108]; Bengio et al., 2025[103]). The findings generally suggest that as models scale across different domains (i.e. model size, data size and training compute increases), their capabilities improve quantitatively following a power law. This implies that even though qualitative improvements may arise in larger models through abilities absent in smaller models, limitations to scale currently define the technological frontier of AI model capabilities.

Computational resources, in particular, play a defining role in the pre-training phase and, to a lesser extent, in the fine-tuning phase (Bengio et al., 2025[103]). Given the natural scarcity of other scalable factors, such as available training data, scaling up compute has been a major driver of AI model capabilities, and long-term improvements in model capabilities can therefore be expected to stem from efficiency improvements in both the hardware and software for compute, as well as compute infrastructure.

Historically, computing power for ICT technologies has been driven by Moore's law, which suggests that the number of transistors on microprocessors doubles every two years (Moore, 1965[109]), an empirical relationship that has been consistently observed throughout the second half of the twentieth century.[15] However, AI training compute has been growing much faster than Moore's law. Since 2012, the computational capabilities used to train modern machine learning systems have grown exponentially, with a doubling time every 3.4 months. This growth is driven by the increasing capabilities of large, compute-intensive AI systems, particularly deep learning models. Advances in hardware have also played a crucial role, with the transition from general-purpose central processing units (CPUs) to specialised processors like graphics processing units (GPUs), tensor processing units (TPUs), and neural processing units (NPUs) enabling more efficient AI training. These specialised processors are optimised for the parallelised computing required by AI models. Additionally, the performance of supercomputers has grown significantly, with the leading supercomputer's computational capacity increasing approximately 630 times from 2009 to 2022, supporting the training of more complex and larger AI models (OECD, 2023[110]). In the context of the compute necessary for deep learning models, using a dataset of over 200 language model evaluations on Wikitext and Penn Treebank over the period 2012-23, Ho et al. (2024[111]) find that the compute required to reach a set performance threshold has halved approximately every 8 months, thus outpacing Moore's law. They further show that the increase in compute made a significant contribution to performance improvements in that period compared to algorithmic progress.

In recent years, generative AI models have also shown an accelerated pace of growth in training compute as compared to past AI models (Figure 4.3). Between 2010 and May 2024, the training compute of AI models, measured in number of mathematical operations (i.e. floating-point operations per second, or FLOPS), has grown about 4.4-fold per year, as compared to a yearly 1.5-fold growth pre-2010 (Epoch, 2024[112]; Sevilla et al., 2022[113]). The scale of growth in compute of the top 10 frontier models (among which Google's Gemini Ultra 1.0 or OpenAI's GPT-4, but also Anthropic's Claude 2) has been at around 4 times per year (Epoch, 2024[112]). When focusing on leading companies in AI development (including OpenAI, Google DeepMind and Meta AI), a similar growth rate is observed, showing that this observation seems to translate to the firm level at the frontier. Meanwhile, other language models catching up to the frontier of AI have demonstrated a faster yearly growth of up to nine-fold.

Figure 4.3. Total training compute used to train notable AI models



Note: A notable model meets any of the following criteria: i) state-of-the-art improvement on a recognised benchmark, ii) highly cited (over 1 000 citations), iii) historical relevance, iv) significant use.
Source: Epoch AI, 'Data on Notable AI Models'. Published online at epoch.ai. Retrieved from 'https://epoch.ai/data/notable-ai-models' [online resource]. Accessed 5 February 2025.

Model capabilities

Since its inception, generative AI has seen rapid improvements in its model capabilities, which has made it both more reliable and applicable for use cases previously not covered. A unique feature of generative AI is the prompt engineering feature, which allows users to provide input prompts continuously and iteratively until the desired output is achieved (Banh and Strobel, 2023[73]). With each iteration process, the model adapts to user preferences and continuously improves to produce content that is tailored to users' desired output. As generative AI models improve, users also adapt their human prompts in response to the models' increased capabilities to achieve their goals more efficiently (Eaman Jahani et al., 2024[114]). While AI-generated prompts reduce the benefits of using the more capable models, with the updating of human prompts by users, new models reach new capabilities with each iteration.

To understand the performance of various generative AI models, several benchmarks have been developed to evaluate models on natural language understanding (NLU), testing models' reading comprehension of human language, a long-standing issue of AI in which it struggled to deal with complex and real-world tasks (Weston et al., 2015[115]). The General Language and Evaluation (GLUE) benchmark was created in 2018 to provide a metric to evaluate model progress on a diverse set of NLU tasks, including question answering, sentiment analysis, textual entailment, and a corresponding online platform for model evaluation, comparison and analysis (Wang et al., 2018[116]). Nonetheless, various models including ELMo, OpenAI GPT and BERT have made such rapid and significant progress over a short span of time that the SuperGLUE benchmark with a set of more difficult language understanding tasks was created only a year later (Wang et al., 2019[117]). The SuperGLUE benchmark is designed to challenge the best models to display advanced reasoning and language generation abilities and to thereby drive further improvements of these models over time. Other benchmarks apply different methods to test models. These include question answering benchmarks such as the crowdsourced Stanford Question Answering Dataset (SQuAD) (Rajpurkar, 2016[118]) and its successor SQuADRUn (Rajpurkar, Jia and Liang, 2018[119]), with testing the model's response for accurateness. Moreover, the Multi-Genre Natural Language Inference (MNLI) benchmark (Williams, Nangia and Bowman, 2018[120]) is a dataset that evaluates NLU in models by testing their ability to determine the relationship between two sentences, which can be classified as either entailment, contradiction or neutral.

Following the advancements in benchmarks like GLUE and SuperGLUE, a shift in the focus of the AI community occurred away from these two benchmarks. In the first GLUE leaderboard, some models surpassed human performance in most areas (Wang et al., 2019[117]). However, even though the leaderboard has been updated, fewer new models have been submitted to the leaderboard, indicating that the limits of benchmarking may have been reached. This led to a decline in interest in improving benchmark scores, with many major commercial models not being submitted and the leaderboard becoming more academic in nature. Additionally, some existing benchmarks have faced criticism for not adequately addressing areas where models need improvement, such as biases, which may even be exacerbated by benchmarking. As a result, developers have started to test their models using different methods, such as adversarial data, which are data intentionally designed to deceive machine learning models into making incorrect predictions or decisions (Bowman and Dahl, 2021[121]).

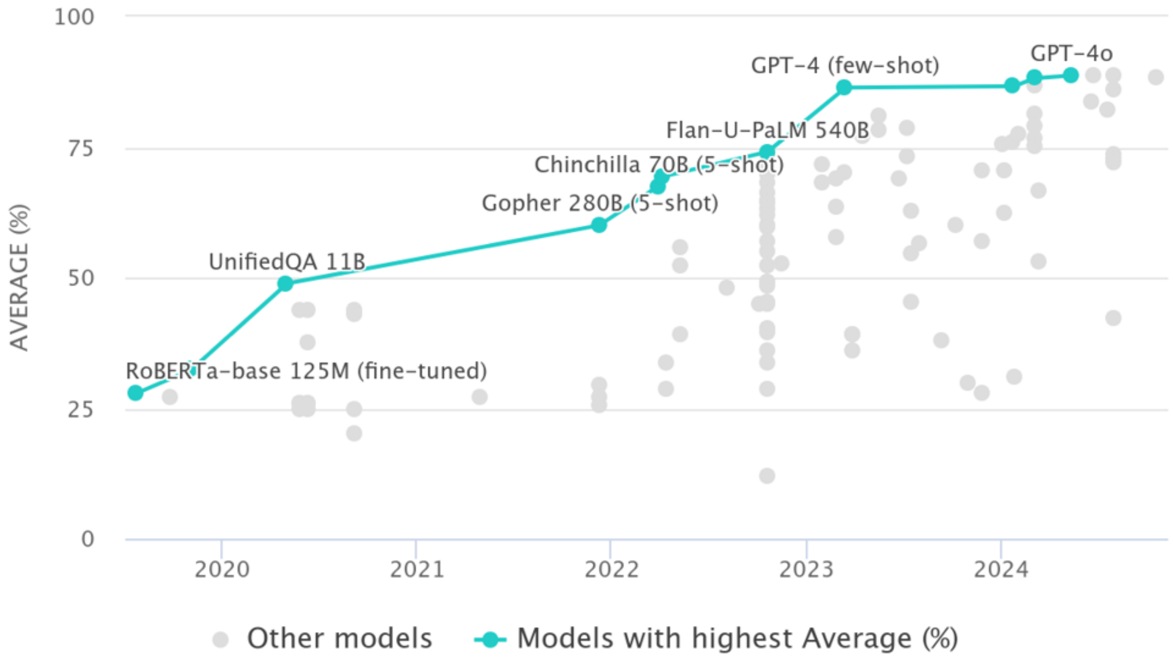
After the introduction of BERT, performance on most tasks in the SuperGLUE benchmark has largely saturated, highlighting the need for new and more challenging evaluation methods. This is a sign that generative AI may have reached a stage in its technological development where it is excelling at tasks previously thought of as a major barrier to adoption and ultimately its usefulness. The Measuring Massive Multitask Language Understanding (MMLU) benchmark seeks to be more challenging than SuperGLUE, yet recent models such as GPT-4o have consistently achieved top scores (see Figure 4.4) (Hendrycks et al., 2021[122]).

More recently, combining various benchmarks such as the MMLU, André et al. (2025[123]) construct a comprehensive AI Economic Frontier that maps quality and model prices, showcasing the most competitive models delivering optimal performance at a given price. Over the past two years, quality-adjusted AI model prices have declined substantially, driven by the emergence of smaller, more efficient models, the availability of open-source solutions, and technological innovations that have reduced hardware costs. Despite rapid innovation and the dominance of leading AI developers, other companies appear to be quickly catching up, showing continuous improvements in model quality alongside price reductions.

Indeed, recent LLMs have been shown to increasingly outperform humans across various domains such as in reading and science. While OpenAI's 2022 GPT-3.5 could answer 73% of reading test questions of the Programme for International Student Assessment (PISA) test and 66% of the science questions, its early 2023 GPT-4 already successfully answered 85% of reading and 84% of science questions, with both models outperforming students (OECD, 2023[124]). While still lagging behind student performance, GPT-4 improved to being able to correctly perform 40% of mathematics tasks from 35% for GPT-3.5. Similarly, AI was able to outperform humans in the literacy and numeracy tests of the OECD Survey of Adult Skills of the Programme for International Assessment of Adult Competencies (PIAAC) as early as 2021, outperforming 90% of adults in literacy and 57-88% of adults in numeracy, with an average 25 percentage point increase since 2016 (OECD, 2023[125]). Additionally, recent work by the OECD's Centre for

Educational Research and Innovation provides an AI capability index across different indicators and domains (OECD, 2025[126]).

Figure 4.4. Models are approaching top scores on MMLU

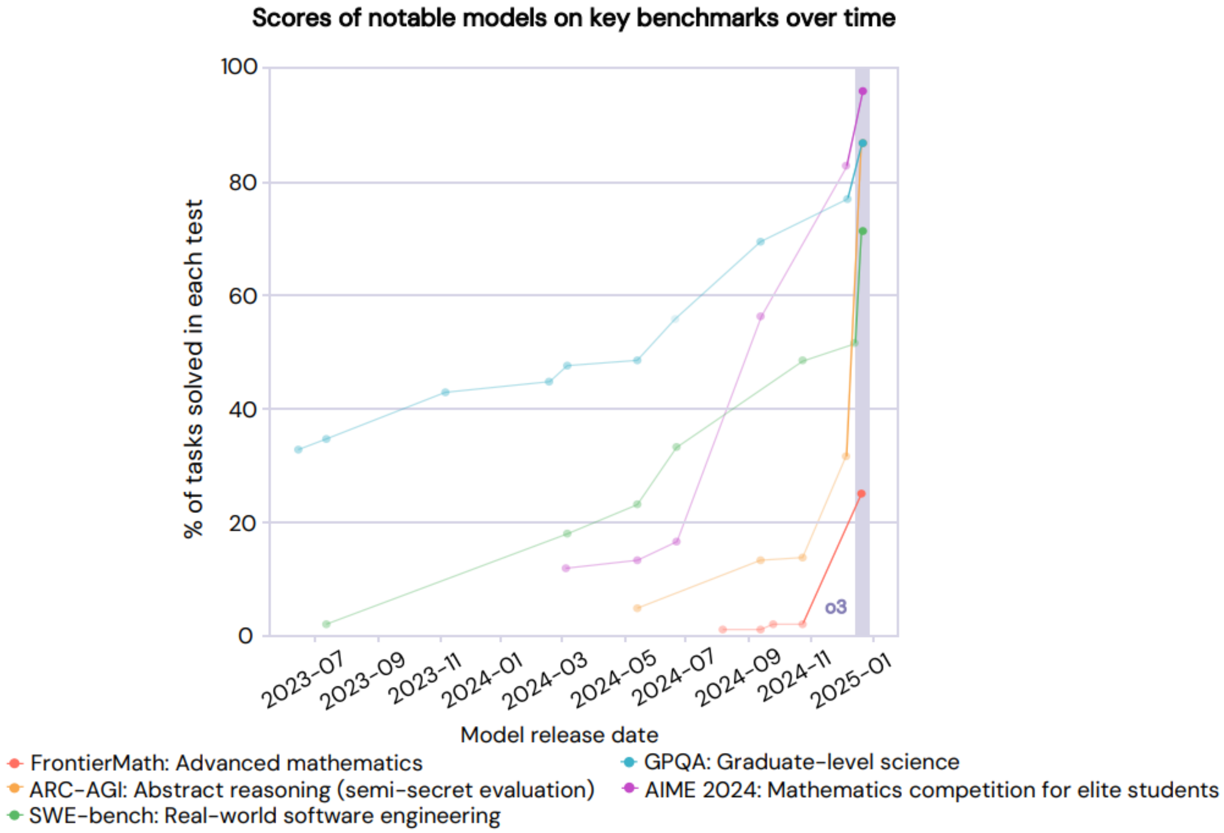


Source: Multi-task Language Understanding on MMLU. Retrieved from 'https://paperswithcode.com/sota/multi-task-language-understanding-on-mmlu'. Accessed 18 February 2025. Based on Hendrycks et al. (2021[122]).

Relatedly, several studies show that LLMs are increasingly capable in occupational tests. For example, Open AI's GPT models performed well on professional certification tests of various professions ranging from accountants, veterinarians, aviation inspectors, real estate appraisers, human resources professionals and financial planners to neurosurgeons, ophthalmologists and medical licenses as well as lawyers, and with GPT-4 consistently outperforming the older GPT-3 and GPT-3.5 models (Noever and Ciolino, 2023[127]; Ali et al., 2023[128]; Antaki et al., 2023[129]; Lin et al., 2023[130]; Nori et al., 2023[131]; OECD, 2023[132]; Eulerich et al., 2023[133]; Katz et al., 2023[134]). More recently, GPT-4o has shown to significantly outperform GPT-4 in the Japanese Dental Examination (Morishita et al., 2024[135]) and Chinese Medical Licensing Examination (Lian, 2024[136]).

Recent developments in newer models even indicate an accelerated improvement in model capabilities across various dimensions. Notably, advancements in reasoning capabilities have laid the foundation for so called LLM-based "AI agents", which are artificial entities with the ability to perceive their environment, make decisions, and take actions with reduced human intervention (Xi et al., 2023[137]). By utilising generative AI in the form of LLMs for reasoning and decision making, such AI agents are increasingly able to take autonomous action in multi-step, complex processes based on high-level objectives (Wang et al., 2024[138]). For example, agentic capabilities benefit from "deep research", or "deep thinking", which makes use of multi-step processes to tackle complex tasks by breaking them down into smaller logical steps and systematically using different approaches to work towards a solution, improving significantly on previous models' reasoning and problem-solving capabilities. OpenAI's o3, released in early 2025, shows drastic improvements even in areas that have so far proven difficult for AI models, as benchmarks in mathematics and abstract reasoning show (Bengio et al., 2025[103]) (see Figure 4.5).

Figure 4.5. Recent models perform increasingly well across various benchmarks



Note: Scores of notable generative AI models on key benchmarks over time, with the latest data point representing OpenAI o3.
Source: International AI Safety Report (Bengio et al., 2025[103]).

Such improvements in the agentic capabilities and performance of LLMs, particularly in reasoning, have led to qualitative changes in which generative AI may impact various fields going forward. These developments represent the evolution of the technology from possessing basic reasoning capabilities to being integrated with action in the form of AI agents, and towards multi-agent coordination (UNESCO, 2025[139]). In such a setting, multiple agents are able to communicate, collaborate and even compete with one another. Recent research on multi-agent coordination in simulation settings shows that allowing multiple agents to coexist gives rise to certain believable individual and social human behaviours among agents (Park et al., 2023[140]; Park et al., 2024[141]). In real-world settings, multi-agent coordination remains an area of ongoing research as the current state of the technology tends to rely on clearly defined objectives and has limitations in handling unpredictable scenarios with noisy inputs.

Potential advancements

While AI agent systems are potentially able to deal with real-world problems in more effective ways than simple language models, they are also more expensive to run (Kapoor et al., 2024[142]). In their current state, this application of generative AI may still have shortcomings, e.g. possibly related to a development towards benchmarks that may not fully reflect real-world needs or lack cost-effectiveness. Given this, advanced generative AI models may need to be evaluated across more dimensions, which also provide an indication of how the technology may potentially advance in the future based on recent developments.

Notably, generative AI models consume large amounts of computational resources and energy both in the training and inference phases. This results in significant environmental costs through energy usage, water consumption and carbon emissions (OECD, 2023[71]). For this reason, concerns have been voiced about the computational burden of deep learning models that trends in expanding compute may soon reach their economic and environmental limits (Thompson et al., 2020[143]). While the training phase tends to be more energy- and carbon-intensive than the inference phase, the relative balance between the two phases critically depends on the widespread usage and scale of generative AI models, which increases overall demand for inference (Luccioni, Jernite and Strubell, 2024[144]). Despite the significant environmental costs of generative AI, research quantifying its overall energy usage and carbon emissions remains relatively limited and early estimates vary due to differing methodologies (see OECD (2023[71]) for a review). As generative AI progresses and newer AI models are released, transparent evaluations to estimate the environmental cost of generative AI models holistically may be critical.

Over time, advances in hardware from CPUs to GPUs, to TPUs and NPUs, appeared to improve the speed and efficiency of training and inference phases (IEA, 2024[145]). UNESCO (2025[139]) highlights the trend towards the development of specialised hardware to improve energy efficiency while maintaining high-performance AI capabilities, and the emergence of small, efficient models that run on local machines or edge devices to bring AI capabilities closer to end-users. While this may improve efficiency, it may come at the cost of reduced model performance. Looking forward, relevantly for the GPT discussion, energy efficiency may be a key dimension on which the technology, including the hardware and model architecture, may improve on while still delivering on model performance.

As the technology further develops, it is may also cover a growing number of application areas and sectors, contributing to its overall pervasiveness and spawning of innovations, which will be further discussed in the next subsection.

Innovation spawning

Another key characteristic of GPTs is *innovation spawning*, referring to the ability of the technology to produce new innovations across sectors. This subsection will discuss key quantitative and qualitative indicators that provide evidence of the innovation spawning trait of generative AI. First, it uses quantitative indicators on generative AI patents to assess whether the technology drives forward innovations across industries, and the extent to which such innovations may generate a positive feedback loop for further innovation in generative AI. Second, it considers how generative AI has revolutionised processes across various fields, which exemplify its GPT characteristic of driving innovations, as well as highlights its potential as a GPT to also provide an invention of a method of invention (IMI).

Generative AI patents

Generative AI has driven innovations in both products and processes across industries. Globally, the number of published generative AI patent families (which refers to single innovations) has increased from less than 800 in 2014 to more than 14,000 in 2023 (WIPO, 2024[79]). Patenting activity also surged with the introduction of transformers in 2017, recording average annual growth of around 45% from 2017 to 2023.[16] To quantitively assess the extent to which the technology drives forward innovations across industries, the analysis reported below focuses on patents published from 2010 to 2020 at the United States Patent and Trademark Office (USPTO), and uses their forward citations as a proxy for downstream innovative applications (further details on data and methodology are available in Box 4.1 below).

Box 4.1. Generative AI patents

Data and methodology

The study focuses on generative AI patent families based on the United States Patent and Trademark Office (USPTO) patent applications that were published from 2010 to 2020. Analysis is conducted at the patent family level so that an invention is only considered once when there are several patent applications corresponding to the same invention filed in different jurisdictions.

The analysis focusses on USPTO data, that is curated within the OECD STI Micro-data Lab infrastructure, as it provides more comprehensive bibliographic data, particularly in terms of citations, compared to other patent offices. Additionally, the USPTO allows software to be patented as such, while the European Patent Office (EPO) only considers “computer implemented inventions” patentable. The jurisdiction has the second highest number of generative AI patents filed.

Generative AI patent families were identified by WIPO (2024[79]), which combined classical patent searches (based on keywords and technology classes on patent documents) with prompts using EconSight’s AI search algorithms, and further refined using a trained BERT classifier. WIPO (2024[79]) further discusses such methodology, including reference to the identification of patents relating to generative AI models (e.g. LLMs), modes (e.g. image/video, text), and applications.

The time frame under analysis (patents published from 2010 to 2020) does not fully cover the more recent boom in generative AI in 2022 as patent data after 2022 is incomplete and there is generally an 18-month lag between the filing and publication of new patents. To analyse the forward citations of patents, 5-year and 3-year citation windows were utilised but citation data for patents published after 2018 and 2020 respectively may be incomplete. The citation windows would have some overlap with the recent boom in generative AI in 2022 (e.g. if a generative AI patent published in 2020 is cited by a non-generative AI patent in 2022, which is itself cited by a generative AI patent in 2023).

The analysis further examines generative AI patents that are also ‘breakthrough’ inventions. The OECD STI Micro-data Lab identifies ‘breakthrough’ patents as patents that feature in the top 1 percent of normalised forward citation counts. Forward citation counts are normalised by the average number of forward citations received by patents from a reference cohort (i.e. patents in the same technology class and same filing year).

Indicators measuring patent quality

To analyse the quality of generative AI patents, indicators that measure their technological generality, originality, scope and radicalness are used (Squicciarini, Dernis and Criscuolo, 2013[146]). By construction, all indices have values between 0 and 1.

- Patent generality is based on a modification of the Hirschman-Herfindahl Index (HHI) and relies on information concerning the number and distribution of technology classes (IPC) of citations received (forward citations). Patents that are cited by subsequent patents belonging to a wide range of technology fields are more general.
- Patent originality relies on backward citations to analyse the breadth of technologies and knowledge that were exploited to develop an invention. Patents that rely on a broader range of technology fields are likely to be more original.
- Patent scope is based on the number of number of distinct technology classes, normalised by the maximum scope value of the patents in the same cohort. Patents with larger patent scope are associated with higher technological and market value.

- Patent radicalness compares the technology classes of a patent with that of its backward citations. Patents that cite earlier patents in fields other than the ones they are in more are likely to be more radical.

Source: OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

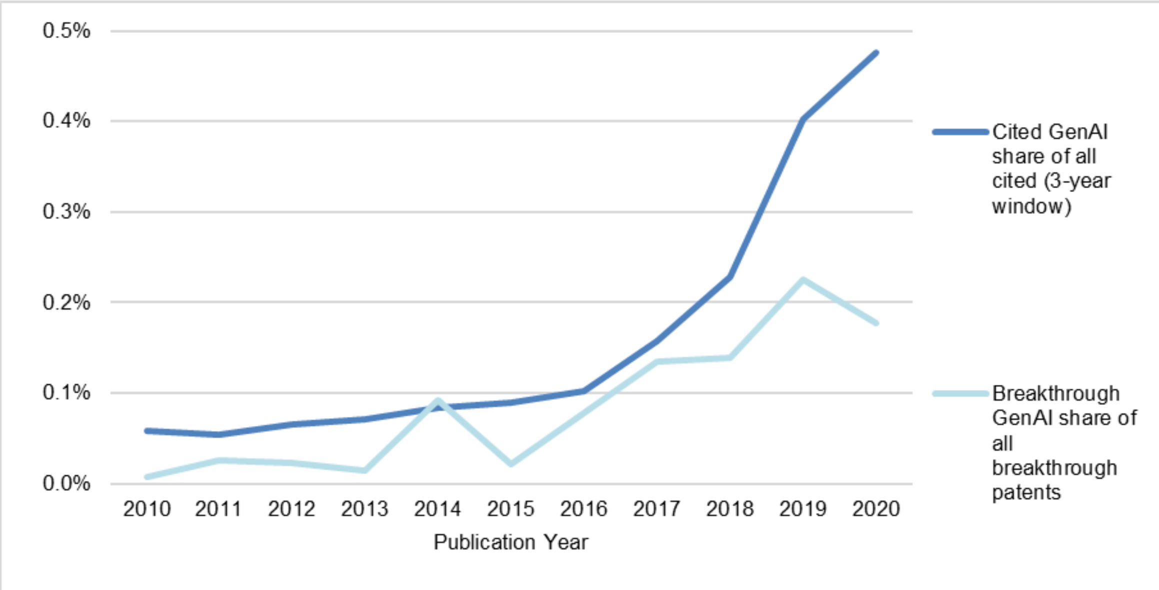
Analysing patents with forward citations, the share of generative AI patents with forward citations as a proportion of all patents with forward citations (using a 3-year citation window) is relatively small but has been steadily increasing from 2010 to 2020, as shown in Figure 4.6. Among generative AI patents, a large share received forward citations, with more than 80% of generative AI patents being cited by other patents (using a 3-year citation window, as shown in Figure A A.1. in Annex A).

Similarly, analysing 'breakthrough' inventions that feature in the top 1 percent of normalised forward citation counts in a reference cohort, the breakthrough generative AI share of all breakthrough patents has also been increasing over this period. Moreover, the number of forward citations received by breakthrough generative AI patents over 2010-2020 is higher than that of other breakthrough patents (using a 3-year citation window, Figure 4.7).

Some initial insights can be derived from these trends on cited and breakthrough generative AI patents. First, the large proportion of generative AI patents being cited suggests the technology's influence in serving as a basis of further technological developments and supporting subsequent innovations that are patented. Second, the presence of breakthrough generative AI innovations, besides cited generative AI ones, shows that some generative AI innovations are high impact and can lead to the creation of many new products or processes. Third, the increasing shares of cited generative AI and breakthrough generative AI patents signal the growing importance of generative AI as a core technology in catalysing new innovations. Fourth, the higher number of forward citations received by breakthrough generative AI compared to those of other technologies shows that leading generative AI inventions appear to spawn subsequent innovation to a greater extent.

Figure 4.6. Generative AI patent share, 2010-20

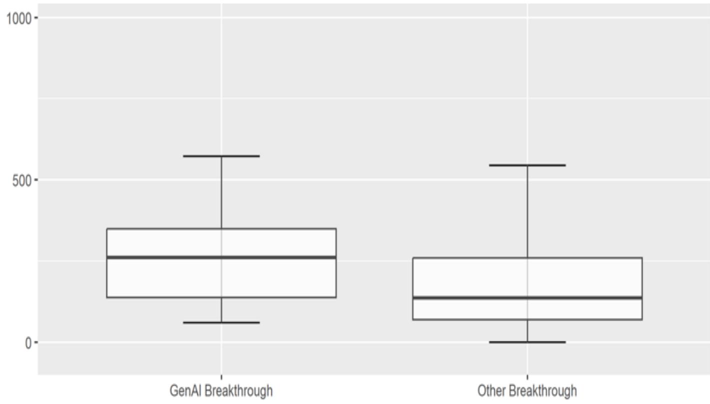
Patents with forward citations (3-year citation window), breakthrough patents (top 1% cited)



Note: Data refer to simple patent families filed at the USPTO. The analysis focusses on the USPTO due to data availability of citations. Breakthrough patents rely on normalised counts of forward citations.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Figure 4.7. Number of forward citations, 2010-20

Generative AI breakthrough, other breakthrough patents (3-year citation window)

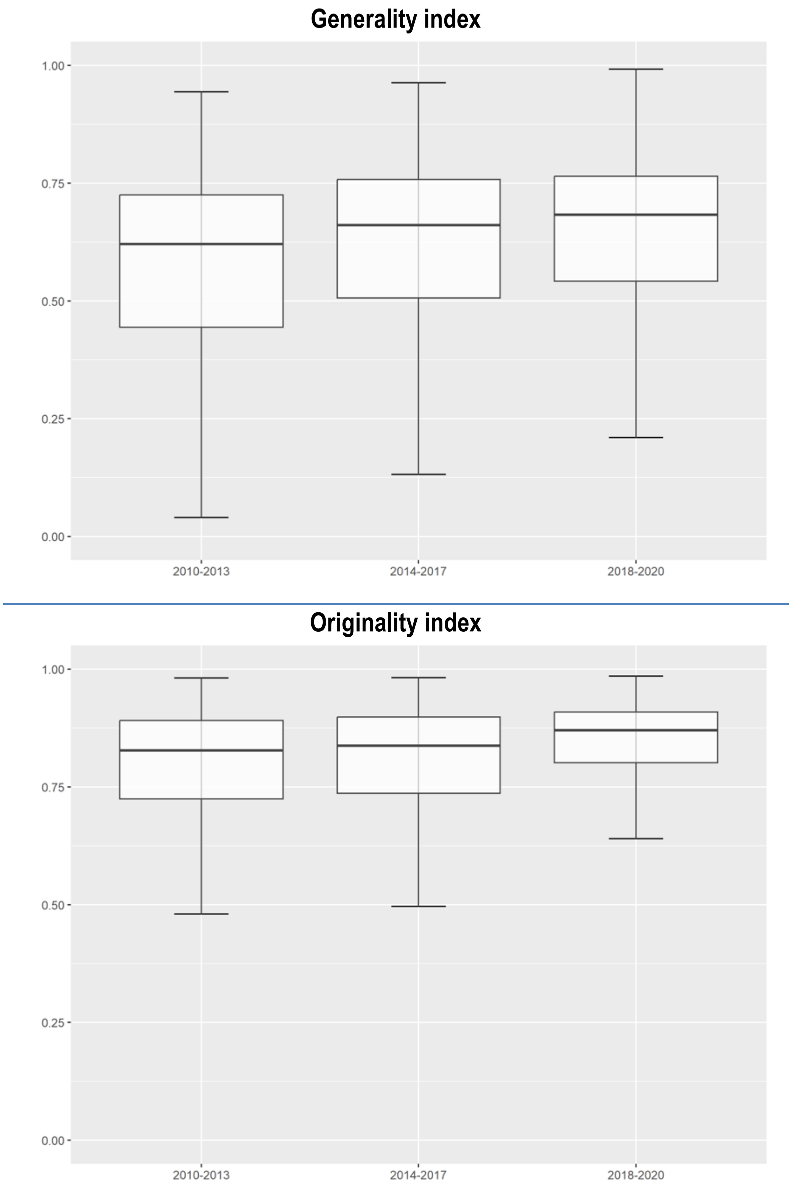


Note: Data refer to simple patent families filed at the USPTO. The analysis focusses on the USPTO due to data availability of citations.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

To further examine the quality of generative AI patents, indicators that measure their technological generality, originality, scope and radicalness are used (refer to Box 4.1 for details on indicators). From 2010 to 2020, generative AI patents became more original and more general over time, while there is less of a clear trend for generative AI patent scope and radicalness (as shown in Figure 4.8 and Figure A.2 in Annex A). Increasing generality and originality indicates that generative AI patents increasingly rely on a larger number of earlier innovations in different technology fields and are increasingly relevant for a larger number of subsequent innovations in different technology fields. This suggests that generative AI innovations not only build on a wider array of prior technological innovations over time but also enable new breakthroughs in a more diverse range of technology fields.

Figure 4.8. Generative AI patent quality, 2010-20

Technological generality and originality indicators



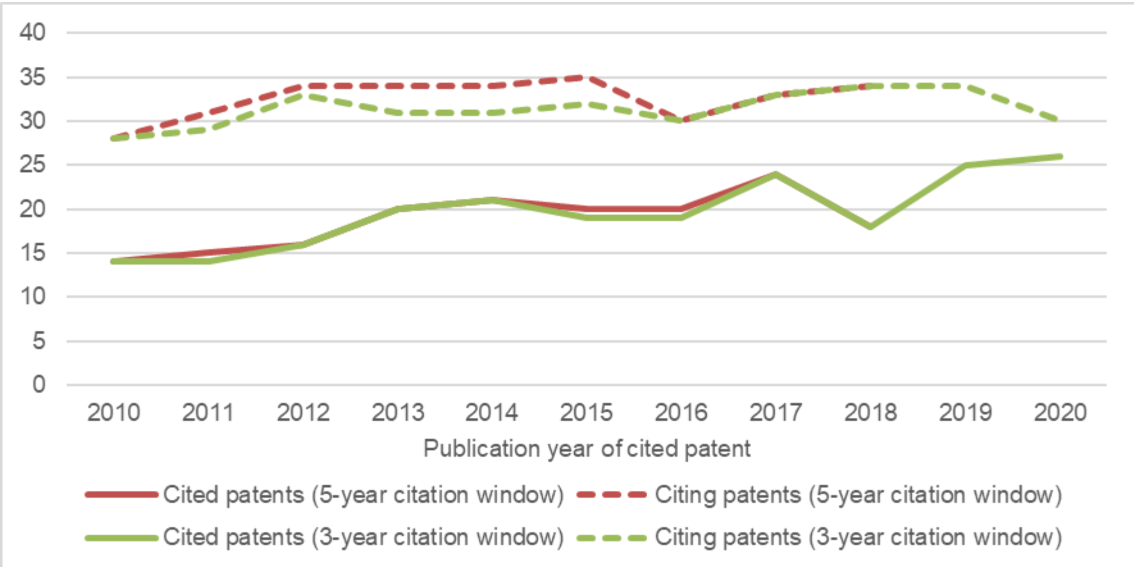
Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. By construction, all indicators presented range between zero and one.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Given the initial evidence that generative AI patents exhibit higher generality over time, the technology fields of generative AI patents that are cited and patents citing those generative AI patents are analysed. From Figure 4.9, it is evident that the forward citations of generative AI patents span multiple WIPO technology fields. Moreover, the number of fields of patents citing generative AI innovations is consistently larger than that the actual fields of the generative AI patents cited. This suggests that generative AI not only spawns innovation within the same technology field but also drives innovative applications across more diverse fields.

Furthermore, focusing on generative AI patents published in 2018 and 2020 (with a 5-year and 3-year citation window respectively), Figure 4.10 (and Figure A.3 in Annex A) show that these span a range of 18 and 26 WIPO fields respectively. A large proportion of the cited patents were in the ‘computer technology’ field, as well as ‘digital communication’, ‘IT methods’, and ‘audio-visual tech’, reflecting the nature of the technology. By contrast, the forward citations of these patents span a broader range of 34 and 30 fields respectively. Besides the aforementioned fields, in fact, a sizeable share of forward citations also fell under ‘control’, ‘medical technology’, ‘telecommunications’, ‘measurement’, ‘transport’, ‘furniture, games’, ‘handling & logistics’, and ‘other consumer goods’ fields. This provides early supporting evidence that while generative AI may fall within certain technology fields, it has a more groundbreaking potential that may be leveraged across a wide range of fields to support the development of new inventions.

Figure 4.9. Number of WIPO technology fields of cited Generative AI patents, 2010-20

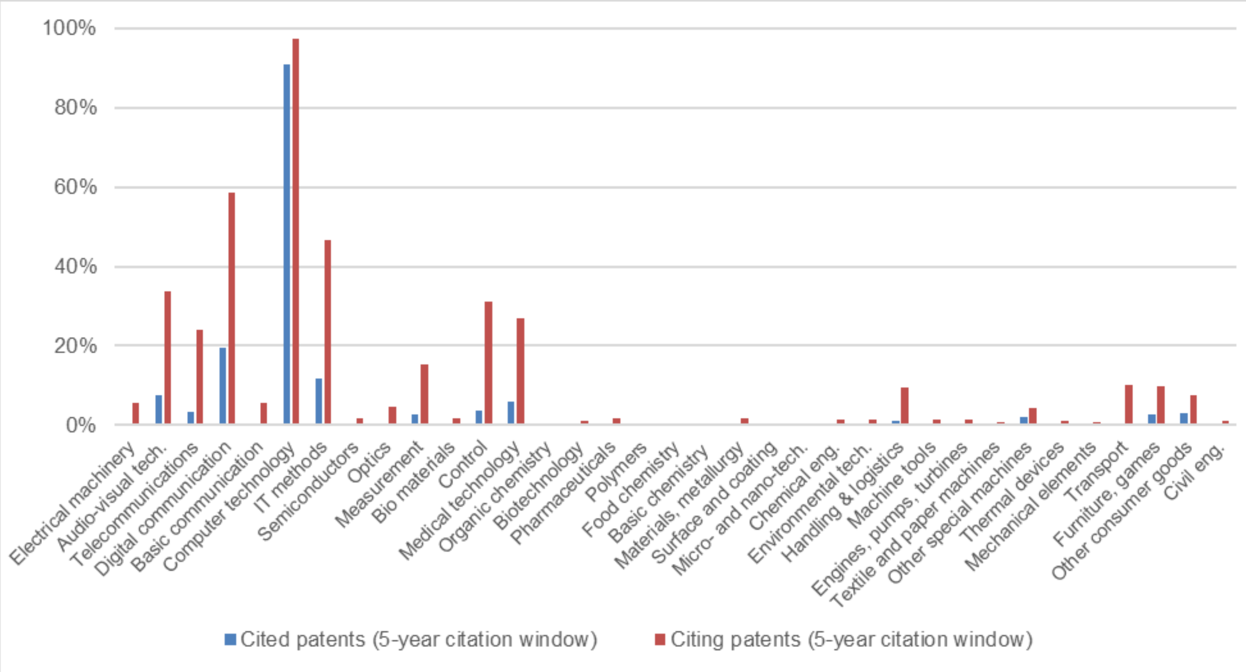
Generative AI patents that are cited and patents citing those generative AI patents (5-year and 3-year citation window)



Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. There are 35 WIPO technology classification fields in total and a patent may have multiple WIPO technology fields. As patent data after 2022 is incomplete, citation data for patents published after 2018 and 2020 may be incomplete for the 5-year and 3-year citation windows respectively.
Source: Authors’ calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Figure 4.10. Share of cited Generative AI patents by WIPO technology fields

Generative AI patents published in 2018 that are cited and patents citing those generative AI patents (5-year citation window)



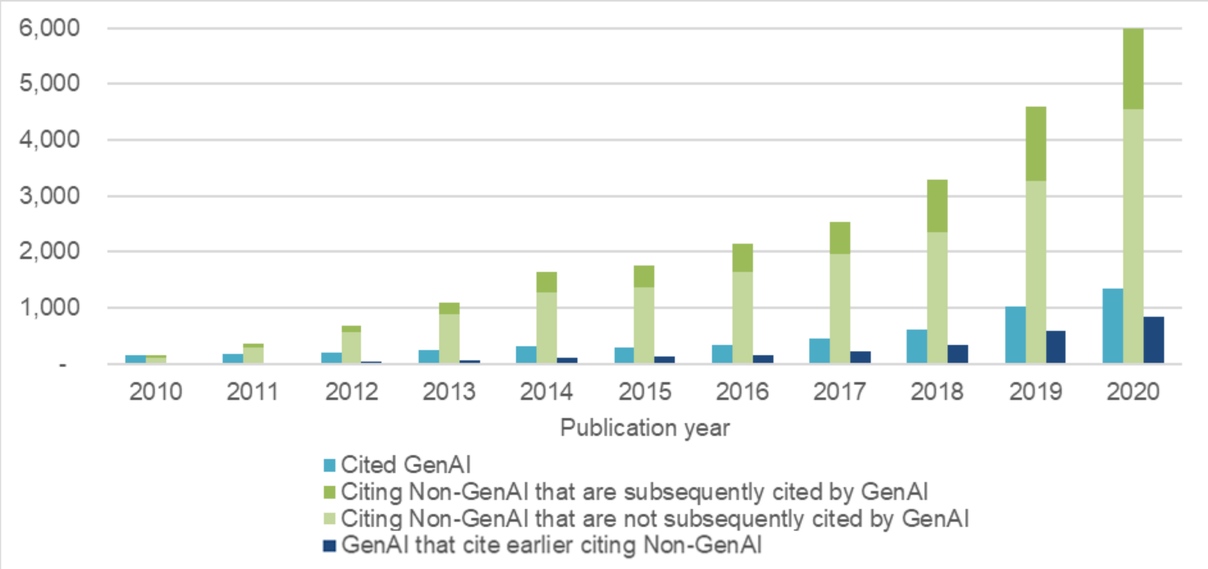
Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. There are 35 WIPO technology classification fields in total and a patent may have multiple WIPO technology fields.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Beyond the evidence that generative AI spawns innovations across a relatively wide range of application sectors, there are signs that such resulting innovation in turn leads to advancements in generative AI itself. This generates a positive feedback loop between the technology and its application sectors, identified by Bresnahan (2024[22]) as being a key consideration in the GPT discussion.

Initial evidence about this phenomenon in the context of generative AI can be seen from the forward citation trends of generative AI patents published from 2010 to 2022 (Figure 4.11). First, the number of generative AI patents being cited is increasing over time. Second, the number of non-generative AI patents, a proxy for innovations in applications sectors, that cite earlier generative AI patents is rising over the same period. Third, the number of generative AI patents that cite non-generative AI patents that were previously citing earlier generative AI technologies is also increasing. While this analysis focuses on patent data and may not fully capture the scale of innovations catalysed by generative AI technologies,[17] the findings suggest that generative AI and its follow-on innovations in application sectors can have a positive feedback innovation loop.

Figure 4.11. Forward citation trends, 2010-22

Cited generative AI patents and patents citing generative AI patents (3-year citation window)



Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. Generative AI patents that do not spawn innovation (i.e. not cited), or that directly spawn generative AI innovations without generating spillovers in other technologies (i.e. cited by generative AI patents directly) are not shown in the figure. As patent data after 2022 is incomplete, citation data for patents published after 2017 may be incomplete due to the two three-year forward citation windows.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Generative-AI-driven process innovations

At the same time, generative AI has revolutionised processes involved in research and innovation, notably including data harmonisation and generation, as well as affected several applied fields, notably including drug discovery, as well as the education system (see Calvino, Reijerink and Samek (Forthcoming[147]) for further discussion). The use cases and evidence presented below further highlight, qualitatively, the role of generative AI for innovation spawning across the economy. The ability of the technology to improve the productivity of research and innovation efforts further suggests that generative AI as a GPT may also have the potential to provide an IMI.

Generative AI supports the generation of novel research ideas, providing opportunities to accelerate scientific discovery and the invention of new products of methods (Stokel-Walker and Noorden, 2023[148]).[18] For instance, a recent large-scale experiment finds that LLM-generated ideas are more novel than ideas generated by human experts, though the former is slightly less feasible (Si, Yang and Hashimoto, 2024[149]). This shows that while the technology may not be able to support the entire research process, it can play a crucial role in supporting and inspiring researchers in the idea generation process and potentially spark off successful projects.

Indeed, a recent study involving a crowdsourcing challenge where participants generated business ideas independently or with generative AI shows that incorporating generative AI in human-centred creative problem solving can augment early innovation (Boussioux et al., 2024[150]). Although human-only crowd solutions displayed higher novelty, solutions developed jointly by humans and generative AI had greater strategic viability, financial and environmental value, and overall quality. Furthermore, human-AI solutions co-created through differentiated search (where human prompts continuously guide LLMs to sequentially generate different outputs from previous iterations) were superior to solutions created through independent search (where humans only provide an initial LLM prompt), as the former mode improves output novelty without compromising on value. This highlights, as further discussed by Calvino, Reijerink and Samek (Forthcoming[147]), the importance of a human-led approach in incorporating generative AI in creative problem solving to drive impactful innovations.

Additional experimental evidence is in fact presented by Calvino, Reijerink and Samek (Forthcoming[147]), further discussing the role of generative AI in enhancing idea generation, creativity, and R&D - in academia and in the private sector -, highlighting a relevant role of prior experience and own knowledge in mediating the use and potential of generative AI for research and innovation. A non-comprehensive list of relevant use cases highlighting such potential is further discussed below.

For social science research, generative AI models also provide a method to generate and test hypotheses in silico (Manning, Zhu and Horton, 2024[151]). Using structural causal models as a basis to design LLM-agents and experiments, generative AI may be leveraged for certain stages of the social science research process (e.g. hypothesis generation, experiment and agent design, running of experiments on generated agents, and results analysis), while also accommodating human inputs (e.g. during hypothesis selection or editing agents). Moreover, LLM-based social simulations show promise in supporting research by generating synthetic human research subjects (Anthis et al., 2025[152]). If key challenges related to the use of LLMs in research are addressed – such as ensuring diversity or avoiding biases, all the while taking into account inaccuracies in out-of-distribution contexts – they could serve as a potentially valuable component of science by complementing traditional research methods (Anthis et al., 2025[152]).

Generative AI models are also capable of harmonising data across multiple sources, which greatly streamlines previously labour-intensive processes (Vert, 2023[153]). Their ability to generate synthetic data may also overcome some challenges related to anonymising sensitive or private data for use, while however creating new ones (e.g. with respect to bias or representativeness).

In the field of drug discovery and development, generative AI can optimise both small molecule and macromolecular drug discovery by generating synthesisable molecules, nucleic acid sequences and proteins with desired structures or functions in a timely and cost-effective manner (Zeng et al., 2022[154]; Vert, 2023[153]). Moreover, generative AI is an enabling technology for digital twins, which are digital replicas of physical entities (e.g. cell lines, organs, entire humans, and animal models) and can be used for experiment simulations or predictions through bi-directional information flows between the entity and its digital twin (Bordukova et al., 2023[155]). For drug discovery, generative AI can support exploration and optimisation of drug candidates in silico, in vitro drug experiments (to determine optimal environmental and biochemical conditions for cell culture performance), histopathology (to predict genetic alterations, treatment response and disease outcomes based on tissue images), and provide an alternative to in vivo drug testing with digital twins (by simulating responses of animal models). For clinical trials, patient digital twins can accelerate decision making by leveraging simulated data, effectively overcoming lengthy patient recruitment processes and the challenges of finding sufficient participants, especially for rare conditions. Looking ahead, growing data availability and algorithmic advances could lead to generative digital twins replacing traditional mechanistic digital twins that are complex to model and computationally intensive (e.g. parameter initialisation).

In the education field, generative AI is fundamentally transforming teaching and learning methods given its potential in adaptive learning experiences (Varsik and Vosberg, 2024[156]). The technology may offer tailored approaches that cater to individual student needs, as seen in intelligent tutoring systems, AI-enabled simulations, AI-powered robots, and AI based systems that identify students at risk of early leaving from education and training. It also enables the creation of engaging and adaptive educational simulations with multiple AI agents, reshaping how knowledge may be delivered, learnt and assessed at scale (Mollick et al., 2024[157]). Specifically, generative AI can help students better understand a topic, facilitate practice, adapt to students' needs and provide personalised feedback. At the same time, AI agents can also help assess students' performance and provide targeted interventions for educators to address gaps in students' knowledge. This may represent a shift away from standard education methods towards more interactive, adaptive and continuous education. This shift may be particularly transformative in highly specialised fields requiring complex, hands-on training such as surgical procedures, as educational simulations may be deployed at scale at lower costs.

5 Policy implications

This paper argues, based on recent literature, use cases and early empirical evidence, that generative AI seems to fulfil, or at least have the potential to fulfil the key GPT's defining characteristics of i) pervasiveness, ii) improvement over time and iii) innovation spawning. Given that the technology's potential as a new GPT, evidence based on earlier GPTs could help shed light on why such transformative potential has not yet translated into aggregate productivity statistics, and on the extent to this may happen in the future.

In fact, while early experimental evidence highlights that generative AI can bring substantial productivity improvements in certain tasks (see e.g. Noy and Zhang (2023[158]); Brynjolfsson, Li and Raymond (2023[159]);[19] see also Calvino, Reijerink and Samek (Forthcoming[147]) for a comprehensive review), aggregate estimates of broader AI's productivity gain tend to often remain milder (Acemoglu, 2024[5]; Filippucci, Gal and Schief, 2024[6]; Briggs and Kodnani, 2023[7]; Aghion and Bunel, 2024[8]). For instance, while early estimates by Briggs and Kodnani (2023[7]) suggest an optimistic view that generative AI may provide a 1.5 percentage point increase in annual labour productivity over a 10-year horizon, Acemoglu (2024[5]) and Filippucci et al (2024[64]) project more cautious estimates on the order of 0.1 percentage point, and 0.4-0.9 percentage point respectively. While these studies consider AI more broadly, generative AI is still in its early stages, with its diffusion and technological potentials yet to fully materialise.

Similarly to other GPTs, there may be a productivity paradox for generative AI (Brynjolfsson, Rock and Syverson, 2019[36]), with productivity gains that may not immediately materialise. The "Productivity J-curve" may reconcile this paradox, as the initial productivity growth of new GPTs is underestimated while unmeasured intangible assets are accumulated. The experience of earlier GPTs shows that their productivity benefits may materialise with significant delays as other complementary transformational changes to the economy take place (Brynjolfsson, Rock and Syverson, 2021[48]; Crafts, 2021[14]; Cardona, Kretschmer and Strobel, 2013[31]). These notably include skill development and organisational changes needed to more effectively leverage the potential of the technology. Nonetheless, the evolution of earlier GPTs provide encouraging signs that generative AI as a GPT could lead to substantial improvements in productivity after complementary investments, innovations and organisational changes are made.

At the same time, generative AI appears to also have the potential to give rise to the invention of a method of invention (IMI). Given this, future increases in productivity in the aggregate economy may not only come from the direct application of generative AI in business operations but may also and relevantly result from increases in the productivity of research and development (R&D). This suggests that the innovation spawning channel may be a relevant driver of future transformational impacts of generative AI. As such, the aggregate productivity implications of the innovation spawning channel may deserve further empirical and theoretical exploration when considering the macroeconomic productivity gains brought about by generative AI.

Furthermore, the full realisation of generative AI's productivity potential in the long-term depends on the ways in which it is developed, deployed and used, which can be critically affected by policymakers. The design and implementation of a comprehensive policy mix aimed at fostering a widespread diffusion and effective use of trustworthy generative AI across firms and industries, supporting its continuous improvement over time, and encouraging follow-on innovations in application sectors appears critical in this context, with key policy levers further discussed below (see also OECD (2024[160]) for further related discussion), in line with the OECD AI Principles' key recommendations for policy makers.

Promoting the diffusion and effective use of trustworthy generative AI across firms and industries

Foster the diffusion of trustworthy generative AI. As the technology advances, continuing to foster its diffusion remains critical to unlock far-reaching economic impacts. Addressing digital divides, ensuring competition and promoting international multi-stakeholder cooperation to ensure that generative AI's use remains trustworthy and respects rights and democratic values remains critical in this context (OECD, 2019[161]). Risk-mitigation measures such as regulation, ethics frameworks, technical AI standardisation, audits and access strategies (Lorenz, Perset and Berryhill, 2023[72]) remain central in the international policy debate (see also (OECD, 2023[162])).

Reinforce the capabilities needed by firms to leverage generative AI's potential. Beyond diffusion, policymakers should focus on reinforcing the capabilities of firms to leverage the potential of the technology. Currently, industries with higher exposure to generative AI appear to be those that are already using AI and other digital technologies more intensively. Firms in these industries may be able to integrate generative AI in their operations more promptly, with more limited reorganisation of their business functions. Policies that strengthen digital infrastructure and support firms' digital transformation more broadly may enable more firms to capitalise on generative AI's potential. The diffusion of generative AI builds in fact on complementary assets, such as digital capabilities, digital infrastructure, and relevantly on skills.

Strengthen human capital as generative AI is adopted. Policymakers should focus on building human capital and strengthen a broad set of worker skills. Generative AI is expected to transform jobs, particularly for higher-skilled workers that are more exposed to the technology. To enable workers and firms to leverage the potential of generative AI, it is crucial to invest in high-quality education and upskilling. Additionally, there is a need to focus on both technical and non-technical skills, including socio-emotional and foundational skills such as problem solving, leadership, or critical thinking, which are key to use generative AI in an effective way. Strengthening managerial capabilities is equally important, particularly in smaller firms, as managers influence technology adoption and optimise conditions for realising generative AI's full benefits. Beyond skills development, governments should ensure fair transitions for workers displaced by generative AI and promote the responsible use of generative AI at work, in line with the OECD AI principles (OECD, 2019[161]).

Supporting continuous improvements of generative AI

Foster generative AI innovation and enable scientific breakthroughs. Policymakers should spur innovation in trustworthy generative AI and encourage interdisciplinary research. Additionally, given the pervasive implications discussed above, policymakers should foster interoperability and the use of standards, and encourage public and private investment in open, representative datasets that respect privacy and data protection, supporting a bias-free R&D environment. As governments invest in developing cutting-edge AI, compute divides can emerge or deepen, reinforcing socioeconomic divides (OECD, 2023[110]). Policymakers can assess technology needs and develop national AI compute plans by considering the aspects of compute capacity, effectiveness and resilience.

Guiding values should be embedded into the AI innovation process. Recent literature stresses the importance of developing AI in ways that are optimal for economic and social outcomes (Acemoglu and Restrepo, 2019[163]). Governments should therefore target innovation not only focusing on challenging technical issues but also and relevantly ensuring that such innovation has beneficial outcomes for all, notably focusing on the related social, legal and ethical implications. AI actors should integrate values throughout the technology's innovation process, taking into account human rights and democratic values as laid out in the OECD AI principles (OECD, 2025[164]).

Encouraging follow-on innovation in sectors leveraging generative AI

Support R&D and innovation more broadly. This can enhance the absorptive capacity of firms, a critical factor for digital technology diffusion and its returns, enabling novel applications of generative AI to emerge across sectors. Policies that encourage data and knowledge sharing across multiple stakeholders, respecting privacy, intellectual property and other rights, are also critical to stimulate research and innovation. In parallel, policymakers should cultivate inclusive ecosystems to ensure that generative AI's benefits extend across the economy and beyond leading firms.

Foster an inclusive ecosystem and policy environment that facilitate the transition from R&D to deployment. Governments should promote a policy environment that facilitates the transition of generative AI systems from R&D to deployment and operation and adapt policy and regulatory frameworks to encourage innovation and competition. Policymakers should create conditions that lower barriers to entry for new firms, facilitate growth for innovative ones, address regulatory challenges around responsible technology development and safeguard intellectual property in the digital economy. More broadly, policymakers should foster the development of, and access to, an inclusive, dynamic, sustainable, and interoperable ecosystem for trustworthy AI, critical not only for its diffusion but also for the extent to which generative AI can be leveraged in novel ways across the economy.

6 Concluding remarks

Through a review of theoretical literature and early empirical evidence, including novel descriptive analysis, this study suggests that generative AI has considerable potential to qualify as a new GPT. In particular, despite the early stage of technology diffusion upon which the discussion and evidence presented are based, generative AI appears to exhibit defining characteristics of GPTs, notably i) pervasiveness, ii) continuous improvement over time, and iii) innovation spawning. Assessing the technology's potential along these dimensions is particularly relevant from a policy perspective, as it informs the debate around AI's transformative potential as well as on the policy levers needed to achieve widespread gains.

In terms of pervasiveness, the applications of generative AI innovation, despite being prevalent in software, span across a considerable number of other areas, ranging from life and medical sciences to banking and finance. While the most recent official figures on usage among firms appear still limited and concentrated in certain sectors, adoption among individuals appears higher, and the technology's displays diffusion potential – based on the tasks it can affect – across diverse sectors that typically account for a considerable share of activities.

Regarding the second characteristic of GPTs, continuous improvement over time, generative AI has seen considerable improvements in compute and model capabilities since its inception that point towards a rapidly evolving technology. Ever more capable models are continuously being released, with the most recent ones excelling at various tasks regarding literacy, numeracy and logical reasoning, often even outperforming humans. Additionally, developments in the technology, such as AI agents, are broadening LLMs' potential, creating new use cases for the technology.

Considering innovation spawning, the analysis has highlighted that generative AI patents are relevantly cited by follow-on innovation in a broad number of application areas. Although these notably include, to a large extent, computer technologies and IT methods, they also considerably go beyond those, with applications ranging from medical technologies to logistics. While the analysis is based on currently available information that may not yet fully reflect the latest technological advances, it already uncovers relevant positive feedback loops from follow-on innovation back to generative AI innovation, which suggest the likely relevance of generative AI as an IMI. Furthermore, generative AI is changing processes related to research and innovation – likely improving their productivity – and, at the same time, affecting several applied fields, notably including drug discovery and education.

Similarly to earlier GPTs, generative AI may exhibit a productivity paradox, with productivity gains that may not materialise immediately and may be dependent on workers' skill development, the implementation of organisational changes and other complementary investments or innovations. The experience of earlier GPTs in fact shows that their productivity benefits may occur with considerable delays as other complementary transformational changes to the economy take place. Nonetheless, the evolution of earlier GPTs seems to provide encouraging signs that generative AI as a GPT could lead to relevant improvements in productivity after complementary investments and innovations are made and businesses are re-organised. In particular, the innovation spawning channel – relevantly combined with the moving technological frontier and continuous improvements over time – could bring relevant productivity gains that go beyond those attributable to the task exposure to the technology.

The full realisation of generative AI's productivity potential in the long-term depends however on the implementation of a policy mix aimed at fostering its widespread diffusion and trustworthy use across firms and sectors, supporting its continuous improvements over time, and reinforcing its ability to spawn innovations in application sectors. The three defining characteristics of GPTs appear in fact particularly relevant from a policy perspective, highlighting the relevance of policy levers that not only foster technological adoption and diffusion, but also enable the effective use of generative AI and its applications across sectors alongside relevant organisational changes, and support innovation at the frontier. As the technology advances, ensuring that generative AI's use remains innovative and trustworthy and respects human rights and democratic values, in line with the OECD AI principles, will remain equally critical. These efforts will be instrumental in unlocking generative AI's full transformative potential as a GPT to drive innovation, enhance productivity, and achieve meaningful societal advancements.

Although the analysis aims at being comprehensive in several respects, future work could further explore some of the aspects discussed in this work. Concerning pervasiveness, beyond continuing to monitor diffusion patterns across firms and sector, future work could more directly relate generative AI's diffusion across firms and use by workers, as well as further link its sectoral exposure with actual generative AI's use. Future work could also zoom in on the innovation spawning channel, exploring patents' citations patterns more broadly, e.g. focusing on the broader set of AI technologies, building upon the recent definition proposed by (Aranda et al., Forthcoming[165]). Additional work could also relate the innovation spawning traits of generative AI, or other GPT characteristics, to those of previous GPTs. Finally, future work could consider embedding the different channels discussed into a macroeconomic model, further accounting for their role in the aggregate implications of generative AI.

Endnotes

[1] Examples include the age of steam and railways made possible by a combination of the steam engine, iron and coal mining technologies and railway construction, as well as more recently the ICT revolution, which was enabled by electronics and telecommunications technologies.

[2] See Kretschmer (2012[166]) for a review of the literature on ICT and productivity growth.

[3] Patent originality relies on backward citations to analyse the breadth of technologies and knowledge that were exploited to develop an invention. Patents that rely on a broader range of technology fields are likely to be more original. Patent generality relies on forward citations received and the range of technology classes of these citing patents. Patents that are cited by subsequent patents belonging to a wide range of technology fields and more general.

[4] Some examples of generative AI products were discussed in Box 3.1.

[5] There is however uncertainty regarding to what extent model performance will continue to scale with data size in the future.

[6] See Filippucci et al. (2024[64]) for further discussion.

[7] See Box 3.1 for examples of generative AI products.

[8] Patent data may not fully capture technological developments, as not all inventions are protected by a patent (e.g. open-source generative AI models and platforms) and not all inventions are patentable. Moreover, the patentability of generative AI technologies varies across patent offices (see Box 4.1 and Aranda et al. (Forthcoming[165]) for details).

[9] The 'software' category also includes patents that cannot be assigned to a specific application.

[10] See also Filippucci et al. (2025[171]) for additional discussion about recent trends in AI adoption in G7 countries, including a focus on the comparability of different indicators and harmonisation efforts, further highlighting relevant increases in adoption and sectoral heterogeneity.

[11] In this context, Crafts (2021[14]) notes that this is largely driven by "GPT capital" rather than more specific capital. GPT capital acts as a driver of productivity by exhibiting a large scope of improvement and can create knowledge spillovers.

[12] Agentic AI uses sophisticated reasoning and iterative planning to autonomously solve complex, multi-step problems, devise strategies and carry out tasks.

[13] Collaborative robots are robots that operate with direct human-robot interaction within a shared space and may have generative AI technologies integrated to adapt their performance to tasks.

[14] Calvino et al. (2024[98]) focus on the sector's AI human capital, AI innovation, (barrier-adjusted) exposure to and use of AI.

[15] In recent years, the extent to which Moore's Law still holds is debated due to physical limits to the size of silicon-based transistors (Leiserson et al., 2020[168]).

[16] While patent family publications rose in 2023, there is generally an 18-month lag between the filing and publication of new patents. As such, the more recent boom in generative AI in 2022 may only accelerate generative patent family publications in 2024 and 2025 (WIPO, 2024[79]).

[17] Patent data may not fully capture technological developments, as not all inventions are protected by a patent and not all inventions are patentable. Moreover, the patentability of generative AI technologies varies across patent offices. Refer to footnote 6.

[18] Relatedly, Besiroglu, Emery-Xu and Thompson (2024[167]) find that deep learning drives productivity in idea production as it is more capital intensive than traditional R&D and may drive up investments in R&D. Refer to OECD (2023[169]) for a comprehensive overview of the use of AI more generally in science, including its current and emerging roles in the productivity of research.

[19] Noy and Zhang (2023[158]) find that exposure to ChatGPT improves the average productivity of workers in carrying out occupation-specific, incentivised writing tasks, by substantially reducing time taken and increasing output quality. Brynjolfsson, Li and Raymond (2023[159]) find that access to Generative AI tools that provide conversational guidance improves the productivity of customer support agents, evidenced by the increase in issues resolved per hour by 14% on average.

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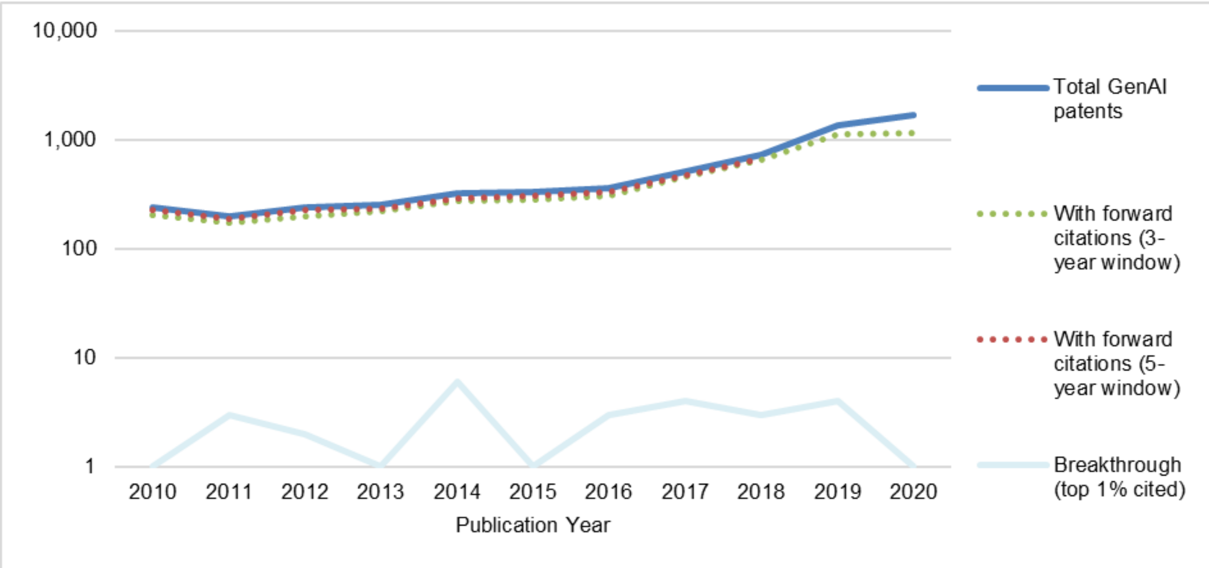
Annex A. Additional figures

Figure A A.1. Generative AI patent count, 2010-20

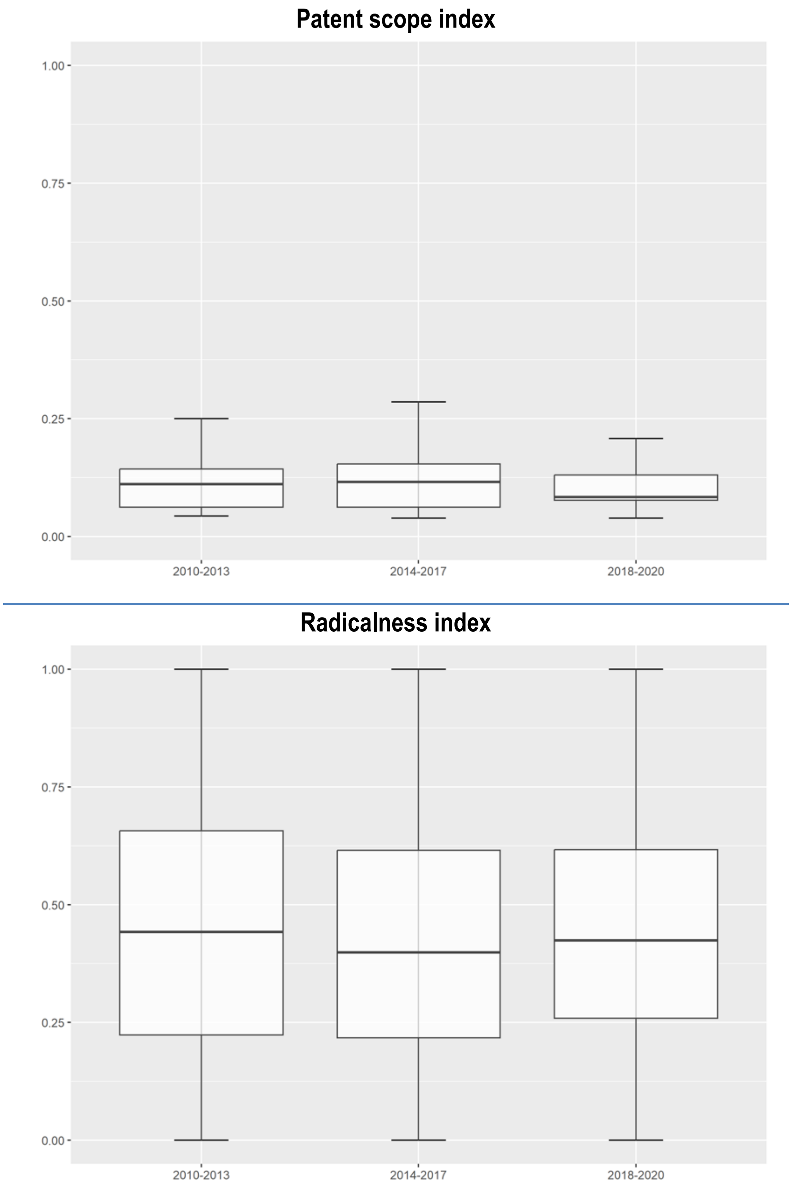
Total patents, patents with forward citations (5-year and 3-year citation window), and breakthrough patents, logarithmic scale



Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. As patent data after 2022 is incomplete, citation data for patents published after 2018 and 2020 may be incomplete for the 5-year and 3-year citation windows respectively. Breakthrough patents rely on normalised counts of forward citations.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Figure A A.2. Generative AI patent quality, 2010-20

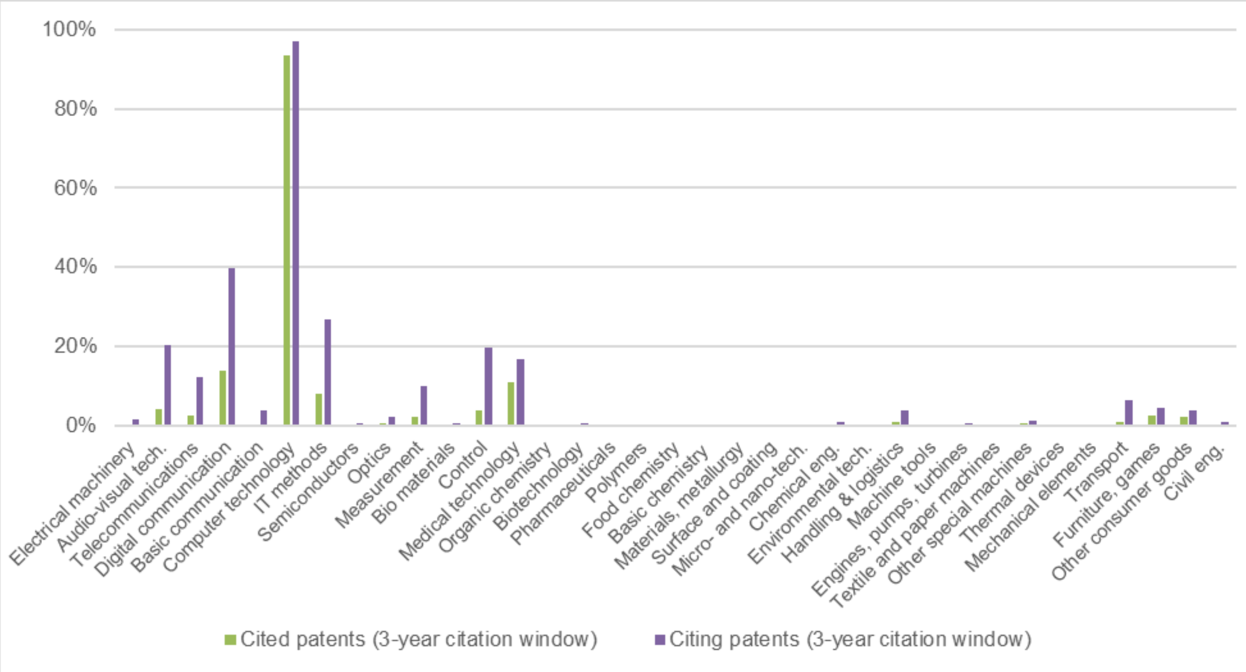
Technological scope and radicalness indicators



Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. By construction, all indicators presented range between zero and one.
Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.

Figure A A.3. Share of cited Generative AI patents by WIPO technology fields

Generative AI patents published in 2020 that are cited and patents citing those generative AI patents (3-year citation window)



Note: Data refer to simple patent families filed at the USPTO that are related to generative AI (based on WIPO data). The analysis focusses on the USPTO due to data availability of citations. There are 35 WIPO technology classification fields in total and a patent may have multiple WIPO technology fields.

Source: Authors' calculations based on data from OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, March 2025, and WIPO, https://doi.org/10.34667/tind.49740.