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The economic potential of generative AI

The next productivity frontier

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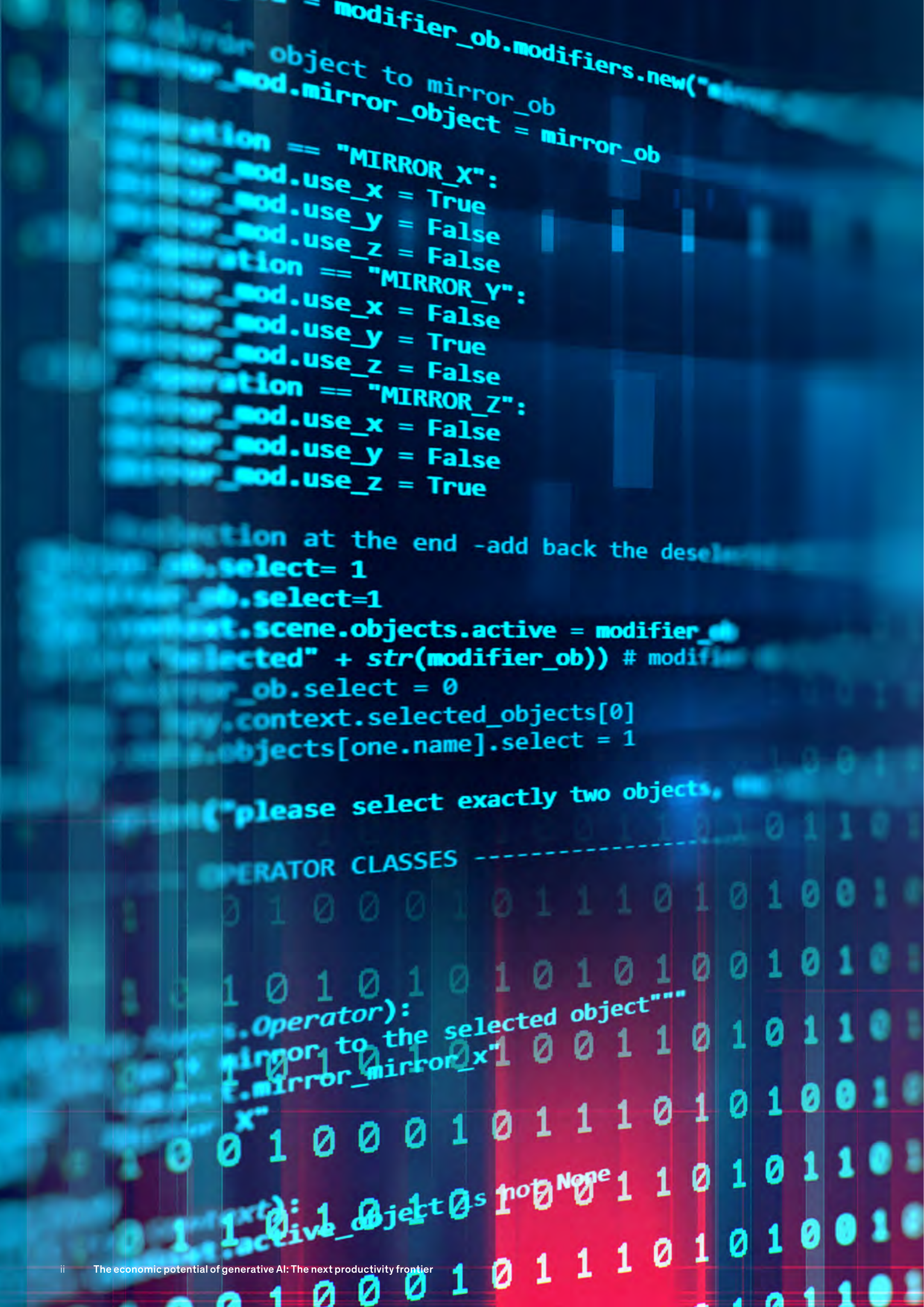
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Contents

Key insights

1. *Generative AI's impact on productivity could add trillions of dollars in value to the global economy.* Our latest research estimates that generative AI could add the equivalent of $2.6 trillion to $4.4 trillion annually across the 63 use cases we analyzed—by comparison, the United Kingdom's entire GDP in 2021 was $3.1 trillion. This would increase the impact of all artificial intelligence by 15 to 40 percent. This estimate would roughly double if we include the impact of embedding generative AI into software that is currently used for other tasks beyond those use cases.

2. *About 75 percent of the value that generative AI use cases could deliver falls across four areas: Customer operations, marketing and sales, software engineering, and R&D.* Across 16 business functions, we examined 63 use cases in which the technology can address specific business challenges in ways that produce one or more measurable outcomes. Examples include generative AI's ability to support interactions with customers, generate creative content for marketing and sales, and draft computer code based on natural-language prompts, among many other tasks.

3. *Generative AI will have a significant impact across all industry sectors.* Banking, high tech, and life sciences are among the industries that could see the biggest impact as a percentage of their revenues from generative AI. Across the banking industry, for example, the technology could deliver value equal to an additional $200 billion to $340 billion annually if the use cases were fully implemented. In retail and consumer packaged goods, the potential impact is also significant at $400 billion to $660 billion a year.

4. *Generative AI has the potential to change the anatomy of work, augmenting the capabilities of individual workers by automating some of their individual activities.* Current generative AI and other technologies have the potential to automate work activities that absorb 60 to 70 percent of employees' time today. In contrast, we previously estimated that technology has the potential to automate half of the time employees spend working.[1] The acceleration in the potential for technical automation is largely due to generative AI's increased ability to understand natural language, which is required for work activities that account for 25 percent of total work time. Thus, generative AI has more impact on knowledge work associated with occupations that have higher wages and educational requirements than on other types of work.

5. *The pace of workforce transformation is likely to accelerate, given increases in the potential for technical automation.* Our updated adoption scenarios, including technology development, economic feasibility, and diffusion timelines, lead to estimates that half of today's work activities could be automated between 2030 and 2060, with a midpoint in 2045, or roughly a decade earlier than in our previous estimates.

6. *Generative AI can substantially increase labor productivity across the economy, but that will require investments to support workers as they shift work activities or change jobs.* Generative AI could enable labor productivity growth of 0.1 to 0.6 percent annually through 2040, depending on the rate of technology adoption and redeployment of worker time into other activities. Combining generative AI with all other technologies, work automation could add 0.2 to 3.3 percentage points annually to productivity growth. However, workers will need support in learning new skills, and some will change occupations. If worker transitions and other risks can be managed, generative AI could contribute substantively to economic growth and support a more sustainable, inclusive world.

7. *The era of generative AI is just beginning.* Excitement over this technology is palpable, and early pilots are compelling. But a full realization of the technology's benefits will take time, and leaders in business and society still have considerable challenges to address. These include managing the risks inherent in generative AI, determining what new skills and capabilities the workforce will need, and rethinking core business processes such as retraining and developing new skills.

Generative AI as a technology catalyst

To grasp what lies ahead requires an understanding of the breakthroughs that have enabled the rise of generative AI, which were decades in the making. ChatGPT, GitHub Copilot, Stable Diffusion, and other generative AI tools that have captured current public attention are the result of significant levels of investment in recent years that have helped advance machine learning and deep learning. This investment undergirds the AI applications embedded in many of the products and services we use every day.

But because AI has permeated our lives incrementally—through everything from the tech powering our smartphones to autonomous-driving features on cars to the tools retailers use to surprise and delight consumers—its progress was almost imperceptible. Clear milestones, such as when AlphaGo, an AI-based program developed by DeepMind, defeated a world champion Go player in 2016, were celebrated but then quickly faded from the public's consciousness.

ChatGPT and its competitors have captured the imagination of people around the world in a way AlphaGo did not, thanks to their broad utility—almost anyone can use them to communicate and create—and preternatural ability to have a conversation with a user. The latest generative AI applications can perform a range of routine tasks, such as the reorganization and classification of data. But it is their ability to write text, compose music, and create digital art that has garnered headlines and persuaded consumers and households to experiment on their own. As a result, a broader set of stakeholders are grappling with generative AI's impact on business and society but without much context to help them make sense of it.

How did we get here? Gradually, then all of a sudden

For the purposes of this report, we define generative AI as applications typically built using foundation models. These models contain expansive artificial neural networks inspired by the billions of neurons connected in the human brain. Foundation models are part of what is called deep learning, a term that alludes to the many deep layers within neural networks. Deep learning has powered many of the recent advances in AI, but the foundation models powering generative AI applications are a step change evolution within deep learning. Unlike previous deep learning models, they can process extremely large and varied sets of unstructured data and perform more than one task.

Foundation models have enabled new capabilities and vastly improved existing ones across a broad range of modalities, including images, video, audio, and computer code. AI trained on these models can perform several functions; it can classify, edit, summarize, answer questions, and draft new content, among other tasks.

Continued innovation will also bring new challenges. For example, the computational power required to train generative AI with hundreds of billions of parameters threatens to become a bottleneck in development.[2] Further, there's a significant move—spearheaded by the open-source community and spreading to the leaders of generative AI companies themselves—to make AI more responsible, which could increase its costs.

Nonetheless, funding for generative AI, though still a fraction of total investments in artificial intelligence, is significant and growing rapidly—reaching a total of $12 billion in the first five months of 2023 alone. Venture capital and other private external investments in generative AI increased by an average compound growth rate of 74 percent annually from 2017 to 2022. During the same period, investments in artificial intelligence overall rose annually by 29 percent, albeit from a higher base.

The rush to throw money at all things generative AI reflects how quickly its capabilities have developed. ChatGPT was released in November 2022. Four months later, OpenAI released a new large language model, or LLM, called GPT-4 with markedly improved capabilities.[3] Similarly, by May 2023, Anthropic's generative AI, Claude, was able to process 100,000 tokens of text, equal to about 75,000 words in a minute—the length of the average novel—compared with roughly 9,000 tokens when it was introduced in March 2023.[4] And in May 2023, Google announced several new features powered by generative AI, including Search Generative Experience and a new LLM called PaLM 2 that will power its Bard chatbot, among other Google products.[5]

From a geographic perspective, external private investment in generative AI, mostly from tech giants and venture capital firms, is largely concentrated in North America, reflecting the continent's current domination of the overall AI investment landscape. Generative AI–related companies based in the United States raised about $8 billion from 2020 to 2022, accounting for 75 percent of total investments in such companies during that period.[6]

Generative AI has stunned and excited the world with its potential for reshaping how knowledge work gets done in industries and business functions across the entire economy. Across functions such as sales and marketing, customer operations, and software development, it is poised to transform roles and boost performance. In the process, it could unlock trillions of dollars in value across sectors from banking to life sciences. We have used two overlapping lenses in this report to understand the potential for generative AI to create value for companies and alter the workforce. The following sections share our initial findings.

Glossary

Application programming interface (API) is a way to programmatically access (usually external) models, data sets, or other pieces of software.

Artificial intelligence (AI) is the ability of software to perform tasks that traditionally require human intelligence.

Artificial neural networks (ANNs) are composed of interconnected layers of software-based calculators known as "neurons." These networks can absorb vast amounts of input data and process that data through multiple layers that extract and learn the data's features.

Deep learning is a subset of machine learning that uses deep neural networks, which are layers of connected "neurons" whose connections have parameters or weights that can be trained. It is especially effective at learning from unstructured data such as images, text, and audio.

Early and late scenarios are the extreme scenarios of our work-automation model. The "earliest" scenario flexes all parameters to the extremes of plausible assumptions, resulting in faster automation development and adoption, and the "latest" scenario flexes all parameters in the opposite direction. The reality is likely to fall somewhere between the two.

Fine-tuning is the process of adapting a pretrained foundation model to perform better in a specific task. This entails a relatively short period of training on a labeled data set, which is much smaller than the data set the model was initially trained on. This additional training allows the model to learn and adapt to the nuances, terminology, and specific patterns found in the smaller data set.

Foundation models (FM) are deep learning models trained on vast quantities of unstructured, unlabeled data that can be used for a wide range of tasks out of the box or adapted to specific tasks through fine-tuning. Examples of these models are GPT-4, PaLM, DALL·E 2, and Stable Diffusion.

Generative AI is AI that is typically built using foundation models and has capabilities that earlier AI did not have, such as the ability to generate content. Foundation models can also be used for nongenerative purposes (for example, classifying user sentiment as negative or positive based on call transcripts) while offering significant improvement over earlier models. For simplicity, when we refer to generative AI in this article, we include all foundation model use cases.

Graphics processing units (GPUs) are computer chips that were originally developed for producing computer graphics (such as for video games) and are also useful for deep learning applications. In contrast, traditional machine learning and other analyses usually run on central processing units (CPUs), normally referred to as a computer's "processor."

Large language models (LLMs) make up a class of foundation models that can process massive amounts of unstructured text and learn the relationships between words or portions of words, known as tokens. This enables LLMs to generate natural-language text, performing tasks such as summarization or knowledge extraction. GPT-4 (which underlies ChatGPT) and LaMDA (the model behind Bard) are examples of LLMs.

Machine learning (ML) is a subset of AI in which a model gains capabilities after it is trained on, or shown, many example data points. Machine learning algorithms detect patterns and learn how to make predictions and recommendations by processing data and experiences, rather than by receiving explicit programming instruction. The algorithms also adapt and can become more effective in response to new data and experiences.

Modality is a high-level data category such as numbers, text, images, video, and audio.

Productivity from labor is the ratio of GDP to total hours worked in the economy. Labor productivity growth comes from increases in the amount of capital available to each worker, the education and experience of the workforce, and improvements in technology.

Prompt engineering refers to the process of designing, refining, and optimizing input prompts to guide a generative AI model toward producing desired (that is, accurate) outputs.

Self-attention, sometimes called intra-attention, is a mechanism that aims to mimic cognitive attention, relating different positions of a single sequence to compute a representation of the sequence.

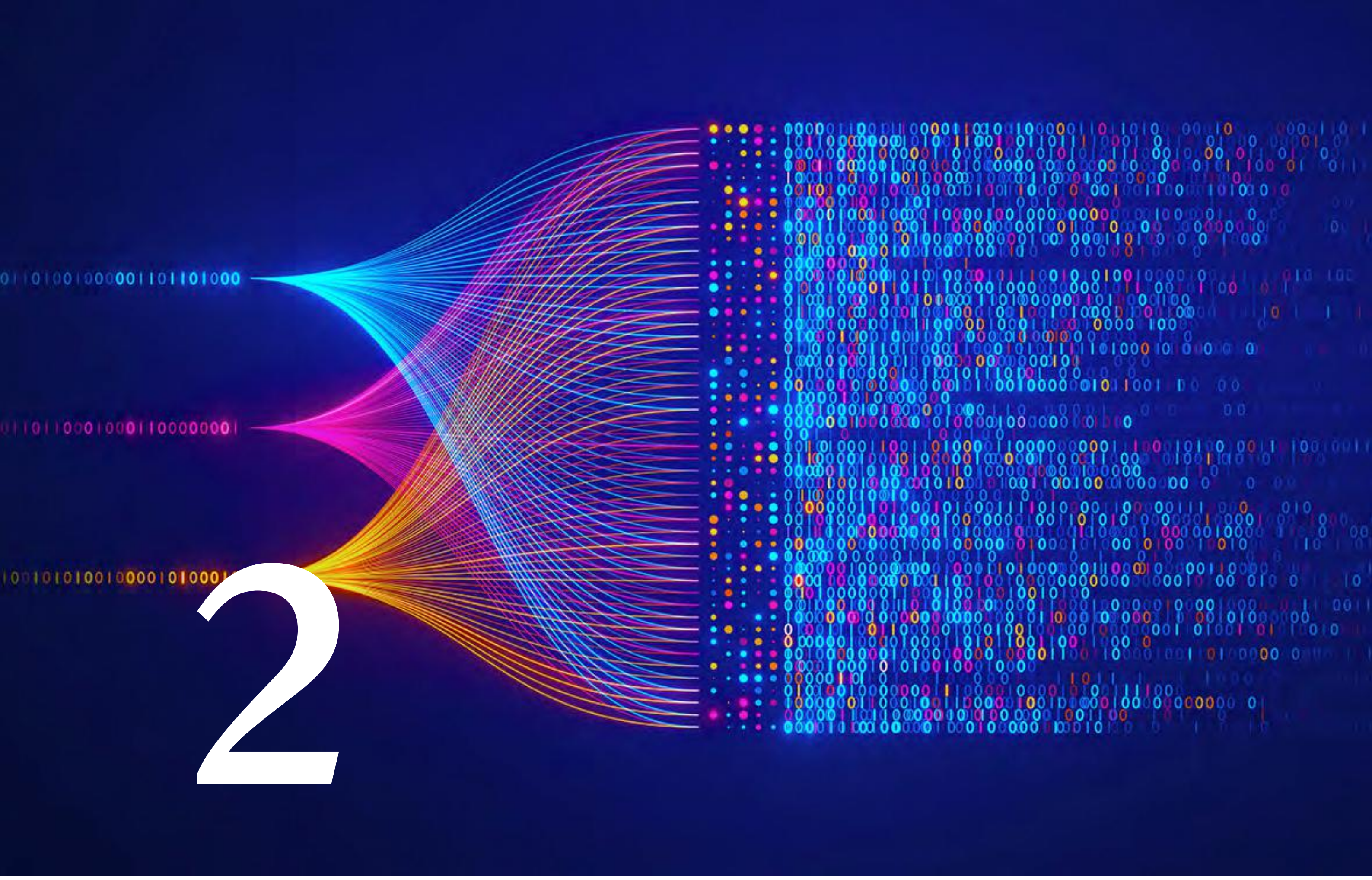
Structured data are tabular data (for example, organized in tables, databases, or spreadsheets) that can be used to train some machine learning models effectively.

Transformers are a relatively new neural network architecture that relies on self-attention mechanisms to transform a sequence of inputs into a sequence of outputs while focusing its attention on important parts of the context around the inputs. Transformers do not rely on convolutions or recurrent neural networks.

Technical automation potential refers to the share of the worktime that could be automated. We assessed the technical potential for automation across the global economy through an analysis of the component activities of each occupation. We used databases published by institutions including the World Bank and the US Bureau of Labor Statistics to break down about 850 occupations into approximately 2,100 activities, and we determined the performance capabilities needed for each activity based on how humans currently perform them.

Use cases are targeted applications to a specific business challenge that produces one or more measurable outcomes. For example, in marketing, generative AI could be used to generate creative content such as personalized emails.

Unstructured data lack a consistent format or structure (for example, text, images, and audio files) and typically require more advanced techniques to extract insights.



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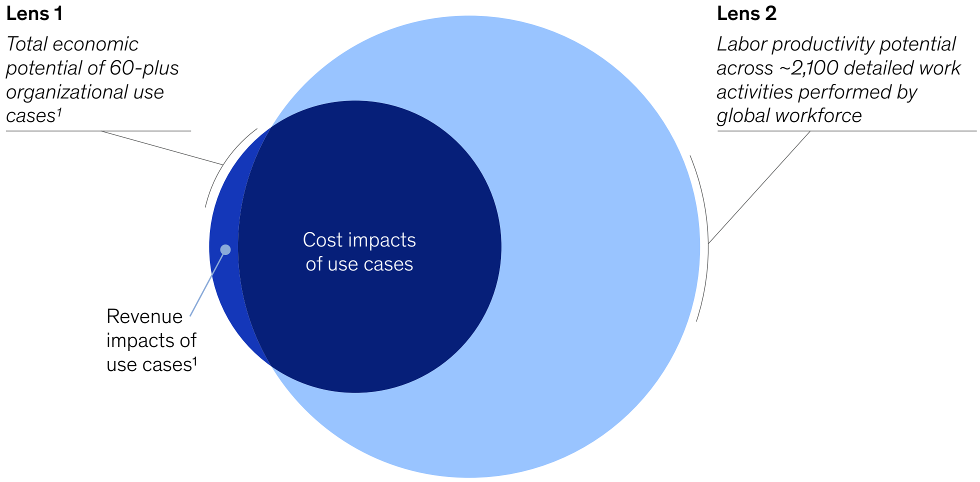
Generative AI use cases across functions and industries

Generative AI is a step change in the evolution of artificial intelligence. As companies rush to adapt and implement it, understanding the technology's potential to deliver value to the economy and society at large will help shape critical decisions. We have used two complementary lenses to determine where generative AI with its current capabilities could deliver the biggest value and how big that value could be (Exhibit 1).

Exhibit 1

The potential impact of generative AI can be evaluated through two lenses.



[1]For quantitative analysis, revenue impacts were recast as productivity increases on the corresponding spend in order to maintain comparability with cost impacts and not to assume additional growth in any particular market.

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The first lens scans use cases for generative AI that organizations could adopt. We define a "use case" as a targeted application of generative AI to a specific business challenge, resulting in one or more measurable outcomes. For example, a use case in marketing is the application of generative AI to generate creative content such as personalized emails, the measurable outcomes of which potentially include reductions in the cost of generating such content and increases in revenue from the enhanced effectiveness of higher-quality content at scale. We identified 63 generative AI use cases spanning 16 business functions that could deliver total value in the range of $2.6 trillion to $4.4 trillion in economic benefits annually when applied across industries.

That would add 15 to 40 percent to the $11.0 trillion to $17.7 trillion of economic value that we now estimate nongenerative artificial intelligence and analytics could unlock. (Our previous estimate from 2017 was that AI could deliver $9.5 trillion to $15.4 trillion in economic value.)

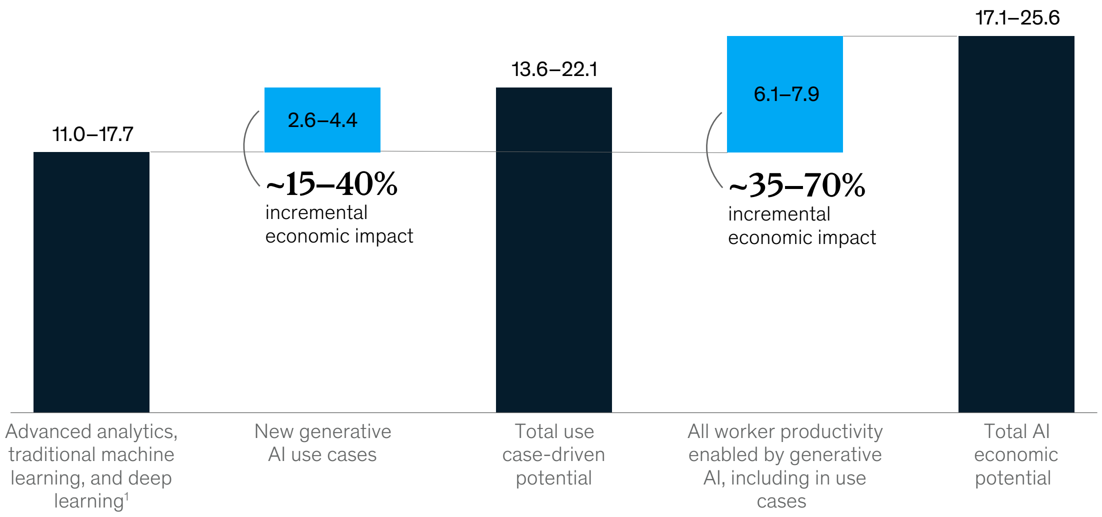
Our second lens complements the first by analyzing generative AI's potential impact on the work activities required in some 850 occupations. We modeled scenarios to estimate when generative AI could perform each of more than 2,100 "detailed work activities"—such as "communicating with others about operational plans or activities"—that make up those occupations across the world economy. This enables us to estimate how the current capabilities of generative AI could affect labor productivity across all work currently done by the global workforce.

Some of this impact will overlap with cost reductions in the use case analysis described above, which we assume are the result of improved labor productivity. Netting out this overlap, the total economic benefits of generative AI—including the major use cases we explored and the myriad increases in productivity that are likely to materialize when the technology is applied across knowledge workers' activities—amounts to $6.1 trillion to $7.9 trillion annually (Exhibit 2).

Exhibit 2

Generative AI could create additional value potential above what could be unlocked by other AI and analytics.

AI's potential impact on the global economy, $ trillion



[1]Updated use case estimates from "Notes from the AI frontier: Applications and value of deep learning," McKinsey Global Institute, April 17, 2018.

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While generative AI is an exciting and rapidly advancing technology, the other applications of AI discussed in our previous report continue to account for the majority of the overall potential value of AI. Traditional advanced-analytics and machine learning algorithms are highly effective at performing numerical and optimization tasks such as predictive modeling, and they continue to find new applications in a wide range of industries. However, as generative AI continues to develop and mature, it has the potential to open wholly new frontiers in creativity and innovation. It has already expanded the possibilities of what AI overall can achieve (please see Box 1, “How we estimated the value potential of generative AI use cases”).

Box 1

How we estimated the value potential of generative AI use cases

To assess the potential value of generative AI, we updated a proprietary McKinsey database of potential AI use cases and drew on the experience of more than 100 experts in industries and their business functions.[1] Our updates examined use cases of generative AI—specifically, how generative AI techniques (primarily transformer-based neural networks) can be used to solve problems not well addressed by previous technologies.

We analyzed only use cases for which generative AI could deliver a significant improvement in the outputs that drive key value. In particular, our estimates of the primary value the technology could unlock do not include use cases for which the sole benefit would be its ability to use natural language. For example, natural-language capabilities would be the key driver of value in a customer service use case but not in a use case optimizing a logistics network, where value primarily arises from quantitative analysis.

We then estimated the potential annual value of these generative AI use cases if they were adopted across the entire economy. For use cases aimed at increasing revenue, such as some of those in sales and marketing, we estimated the economy-wide value generative AI could deliver by increasing the productivity of sales and marketing expenditures.

Our estimates are based on the structure of the global economy in 2022 and do not consider the value generative AI could create if it produced entirely new product or service categories.

[1] “Notes from the AI frontier: Applications and value of deep learning,” McKinsey Global Institute, April 17, 2018.

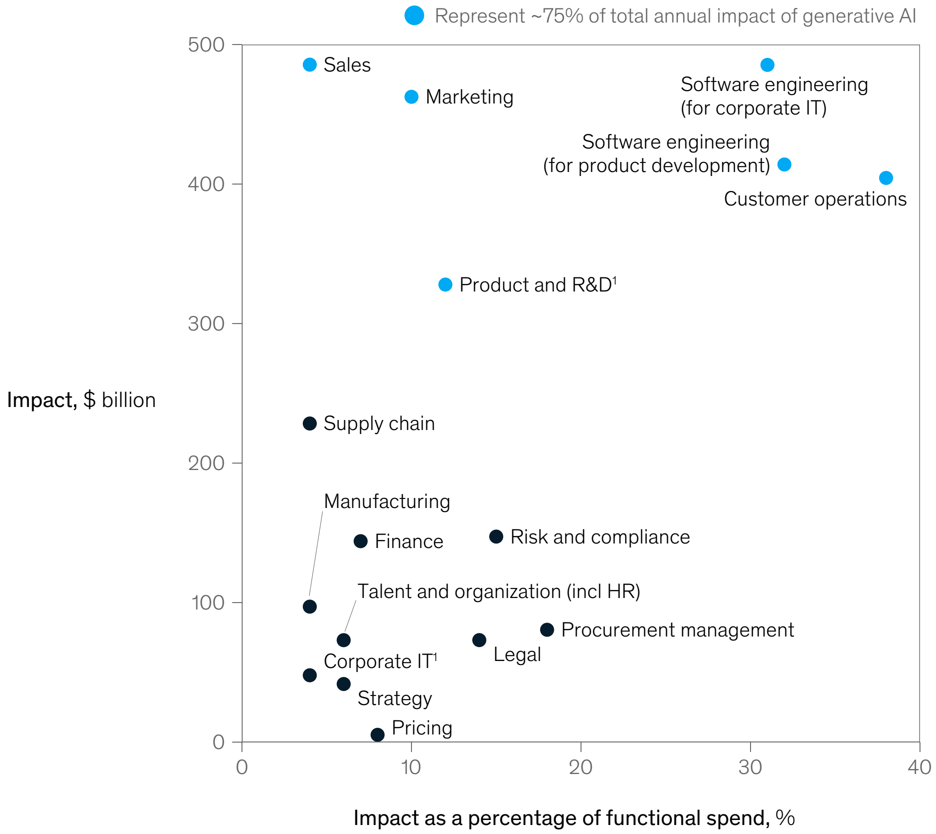
In this chapter, we highlight the value potential of generative AI across two dimensions: business function and modality.

Value potential by function

While generative AI could have an impact on most business functions, a few stand out when measured by the technology's impact as a share of functional cost (Exhibit 3). Our analysis of 16 business functions identified just four—customer operations, marketing and sales, software engineering, and research and development—that could account for approximately 75 percent of the total annual value from generative AI use cases.

Exhibit 3

Using generative AI in just a few functions could drive most of the technology's impact across potential corporate use cases.



Note: Impact is averaged.
[1]Excluding software engineering.
Source: Comparative Industry Service (CIS), IHS Markit; Oxford Economics; McKinsey Corporate and Business Functions database; McKinsey Manufacturing and Supply Chain 360; McKinsey Sales Navigator; Ignite, a McKinsey database; McKinsey analysis

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Notably, the potential value of using generative AI for several functions that were prominent in our previous sizing of AI use cases, including manufacturing and supply chain functions, is now much lower.[7] This is largely explained by the nature of generative AI use cases, which exclude most of the numerical and optimization applications that were the main value drivers for previous applications of AI.

Generative AI as a virtual expert

In addition to the potential value generative AI can deliver in function-specific use cases, the technology could drive value across an entire organization by revolutionizing internal knowledge management systems. Generative AI's impressive command of natural-language processing can help employees retrieve stored internal knowledge by formulating queries in the same way they might ask a human a question and engage in continuing dialogue. This could empower teams to quickly access relevant information, enabling them to rapidly make better-informed decisions and develop effective strategies.

In 2012, the McKinsey Global Institute (MGI) estimated that knowledge workers spent about a fifth of their time, or one day each work week, searching for and gathering information. If generative AI could take on such tasks, increasing the efficiency and effectiveness of the workers doing them, the benefits would be huge. Such virtual expertise could rapidly "read" vast libraries of corporate information stored in natural language and quickly scan source material in dialogue with a human who helps fine-tune and tailor its research, a more scalable solution than hiring a team of human experts for the task.

Following are examples of how generative AI could produce operational benefits as a virtual expert in a handful of use cases.

In addition to the potential value generative AI can deliver in specific use cases, the technology could drive value across an entire organization by revolutionizing internal knowledge management systems.

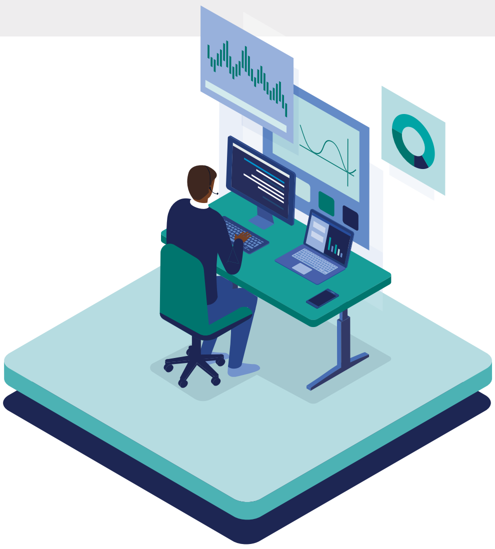
How customer operations could be transformed

Customer self-service interactions

Customer interacts with a humanlike chatbot that delivers immediate, personalized responses to complex inquiries, ensuring a consistent brand voice regardless of customer language or location.

Customer–agent interactions

Human agent uses AI-developed call scripts and receives real-time assistance and suggestions for responses during phone conversations, instantly accessing relevant customer data for tailored and real-time information delivery.



Agent self-improvement

Agent receives a summarization of the conversation in a few succinct points to create a record of customer complaints and actions taken.

Agent uses automated, personalized insights generated by AI, including tailored follow-up messages or personalized coaching suggestions.

Customer operations
Generative AI has the potential to revolutionize the entire customer operations function, improving the customer experience and agent productivity through digital self-service and enhancing and augmenting agent skills. The technology has already gained traction in customer service because of its ability to automate interactions with customers using natural language. Research found that at one company with 5,000 customer service agents, the application of generative AI increased issue resolution by 14 percent an hour and reduced the time spent handling an issue by 9 percent.[8] It also reduced agent attrition and requests to speak to a manager by 25 percent. Crucially, productivity and quality of service improved most among less-experienced agents, while the AI assistant did not increase—and sometimes decreased—the productivity and quality metrics of more highly skilled agents. This is because AI assistance helped less-experienced agents communicate using techniques similar to those of their higher-skilled counterparts.

The following are examples of the operational improvements generative AI can have for specific use cases:

— **Customer self-service.** Generative AI–fueled chatbots can give immediate and personalized responses to complex customer inquiries regardless of the language or location of the customer. By improving the quality and effectiveness of interactions via automated channels, generative AI could automate responses to a higher percentage of customer inquiries, enabling customer care teams to take on inquiries that can only be resolved by a human agent. Our research found that roughly half of customer contacts made by banking, telecommunications, and utilities companies in North America are already handled by machines, including but not exclusively AI. We estimate that generative AI could further reduce the volume of human-serviced contacts by up to 50 percent, depending on a company's existing level of automation.

— **Resolution during initial contact.** Generative AI can instantly retrieve data a company has on a specific customer, which can help a human customer service representative more successfully answer questions and resolve issues during an initial interaction.

— **Reduced response time.** Generative AI can cut the time a human sales representative spends responding to a customer by providing assistance in real time and recommending next steps.

— **Increased sales.** Because of its ability to rapidly process data on customers and their browsing histories, the technology can identify product suggestions and deals tailored to customer preferences. Additionally, generative AI can enhance quality assurance and coaching by gathering insights from customer conversations, determining what could be done better, and coaching agents.

We estimate that applying generative AI to customer care functions could increase productivity at a value ranging from 30 to 45 percent of current function costs.

Our analysis captures only the direct impact generative AI might have on the productivity of customer operations. It does not account for potential knock-on effects the technology may have on customer satisfaction and retention arising from an improved experience, including better understanding of the customer's context that can assist human agents in providing more personalized help and recommendations.

How marketing and sales could be transformed

Strategization

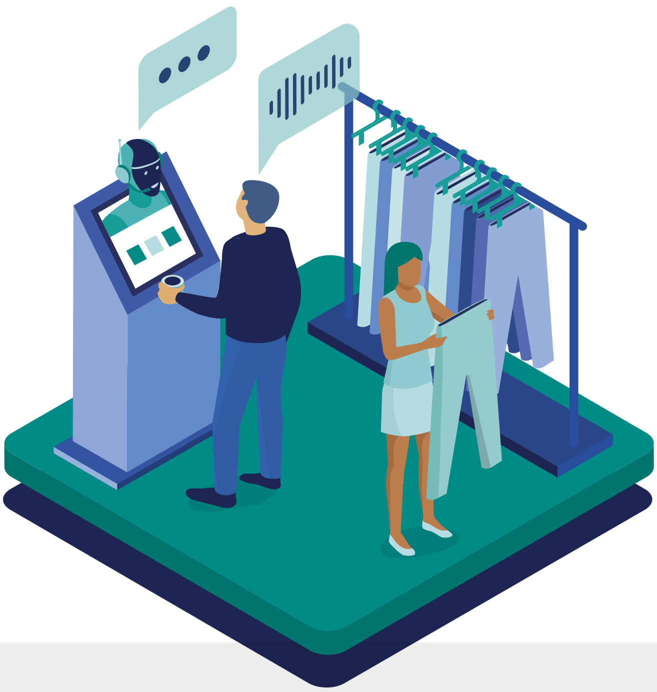
Sales and marketing professionals efficiently gather market trends and customer information from unstructured data sources (for example, social media, news, research, product information, and customer feedback) and draft effective marketing and sales communications.

Awareness

Customers see campaigns tailored to their segment, language, and demographic.

Consideration

Customers can access comprehensive information, comparisons, and dynamic recommendations, such as personal "try ons."



Conversion

Virtual sales representatives enabled by generative AI emulate humanlike qualities—such as empathy, personalized communication, and natural language processing—to build trust and rapport with customers.

Retention

Customers are more likely to be retained with customized messages and rewards, and they can interact with AI-powered customer-support chatbots that manage the relationship proactively, with fewer escalations to human agents.

Marketing and sales

Generative AI has taken hold rapidly in marketing and sales functions, in which text-based communications and personalization at scale are driving forces. The technology can create personalized messages tailored to individual customer interests, preferences, and behaviors, as well as do tasks such as producing first drafts of brand advertising, headlines, slogans, social media posts, and product descriptions.

However, introducing generative AI to marketing functions requires careful consideration. For one thing, mathematical models trained on publicly available data without sufficient safeguards against plagiarism, copyright violations, and branding recognition risks infringing on intellectual property rights. A virtual try-on application may produce biased representations of certain demographics because of limited or biased training data. Thus, significant human oversight is required for conceptual and strategic thinking specific to each company's needs.

Potential operational benefits from using generative AI for marketing include the following:

— **Efficient and effective content creation.** Generative AI could significantly reduce the time required for ideation and content drafting, saving valuable time and effort. It can also facilitate consistency across different pieces of content, ensuring a uniform brand voice, writing style, and format. Team members can collaborate via generative AI, which can integrate their ideas into a single cohesive piece. This would allow teams to significantly enhance personalization of marketing messages aimed at different customer segments, geographies, and demographics. Mass email campaigns can be instantly translated into as many languages as needed, with different imagery and messaging depending on the audience. Generative AI's ability to produce content with varying specifications could increase customer value, attraction, conversion, and retention over a lifetime and at a scale beyond what is currently possible through traditional techniques.

— **Enhanced use of data.** Generative AI could help marketing functions overcome the challenges of unstructured, inconsistent, and disconnected data—for example, from different databases—by interpreting abstract data sources such as text, image, and varying structures. It can help marketers better use data such as territory performance, synthesized customer feedback, and customer behavior to generate data-informed marketing strategies such as targeted customer profiles and channel recommendations. Such tools could identify and synthesize trends, key drivers, and market and product opportunities from unstructured data such as social media, news, academic research, and customer feedback.

— **SEO optimization.** Generative AI can help marketers achieve higher conversion and lower cost through search engine optimization (SEO) for marketing and sales technical components such as page titles, image tags, and URLs. It can synthesize key SEO tokens, support specialists in SEO digital content creation, and distribute targeted content to customers.

— **Product discovery and search personalization.** With generative AI, product discovery and search can be personalized with multimodal inputs from text, images and speech, and deep understanding of customer profiles. For example, technology can leverage individual user preferences, behavior, and purchase history to help customers discover the most relevant products and generate personalized product descriptions. This would allow CPG, travel, and retail companies to improve their ecommerce sales by achieving higher website conversion rates.

We estimate that generative AI could increase the productivity of the marketing function with a value between 5 and 15 percent of total marketing spending.

Our analysis of the potential use of generative AI in marketing doesn't account for knock-on effects beyond the direct impacts on productivity. Generative AI–enabled synthesis could provide higher-quality data insights, leading to new ideas for marketing campaigns and better-targeted customer segments. Marketing functions could shift resources to producing higher-quality content for owned channels, potentially reducing spending on external channels and agencies.

Generative AI could also change the way both B2B and B2C companies approach sales. The following are two use cases for sales:

— **Increase probability of sale.** Generative AI could identify and prioritize sales leads by creating comprehensive consumer profiles from structured and unstructured data and suggesting actions to staff to improve client engagement at every point of contact. For example, generative AI could provide better information about client preferences, potentially improving close rates.

— **Improve lead development.** Generative AI could help sales representatives nurture leads by synthesizing relevant product sales information and customer profiles and creating discussion scripts to facilitate customer conversation, including up- and cross-selling talking points. It could also automate sales follow-ups and passively nurture leads until clients are ready for direct interaction with a human sales agent.

Our analysis suggests that implementing generative AI could increase sales productivity by approximately 3 to 5 percent of current global sales expenditures.

This analysis may not fully account for additional revenue that generative AI could bring to sales functions. For instance, generative AI's ability to identify leads and follow-up capabilities could uncover new leads and facilitate more effective outreach that would bring in additional revenue. Also, the time saved by sales representatives due to generative AI's capabilities could be invested in higher-quality customer interactions, resulting in increased sales success.

Generative AI as a virtual collaborator
In other cases, generative AI can drive value by working in partnership with workers, augmenting their work in ways that accelerate their productivity. Its ability to rapidly digest mountains of data and draw conclusions from it enables the technology to offer insights and options that can dramatically enhance knowledge work. This can significantly speed up the process of developing a product and allow employees to devote more time to higher-impact tasks.

Generative AI could increase sales productivity by 3 to 5 percent of current global sales expenditures.

How software engineering could be transformed

Inception and planning

Software engineers and product managers use generative AI to assist in analyzing, cleaning, and labeling large volumes of data, such as user feedback, market trends, and existing system logs.

System design

Engineers use generative AI to create multiple IT architecture designs and iterate on the potential configurations, accelerating system design, and allowing faster time to market.

Coding

Engineers are assisted by AI tools that can code, reducing development time by assisting with drafts, rapidly finding prompts, and serving as an easily navigable knowledge base.

Testing

Engineers employ algorithms that can enhance functional and performance testing to ensure quality and can generate test cases and test data automatically.

Maintenance

Engineers use AI insights on system logs, user feedback, and performance data to help diagnose issues, suggest fixes, and predict other high-priority areas of improvement.

Software engineering
Treating computer languages as just another language opens new possibilities for software engineering. Software engineers can use generative AI in pair programming and to do augmented coding and train LLMs to develop applications that generate code when given a natural-language prompt describing what that code should do.

Software engineering is a significant function in most companies, and it continues to grow as all large companies, not just tech titans, embed software in a wide array of products and services. For example, much of the value of new vehicles comes from digital features such as adaptive cruise control, parking assistance, and IoT connectivity.

According to our analysis, the direct impact of AI on the productivity of software engineering could range from 20 to 45 percent of current annual spending on the function. This value would arise primarily from reducing time spent on certain activities, such as generating initial code drafts, code correction and refactoring, root-cause analysis, and generating new system designs. By accelerating the coding process, generative AI could push the skill sets and capabilities needed in software engineering toward code and architecture design. One study found that software developers using Microsoft's GitHub Copilot completed tasks 56 percent faster than those not using the tool.[9] An internal McKinsey empirical study of software engineering teams found those who were trained to use generative AI tools rapidly reduced the time needed to generate and refactor code—and engineers also reported a better work experience, citing improvements in happiness, flow, and fulfillment.

Our analysis did not account for the increase in application quality and the resulting boost in productivity that generative AI could bring by improving code or enhancing IT architecture—which can improve productivity across the IT value chain. However, the quality of IT architecture still largely depends on software architects, rather than on initial drafts that generative AI's current capabilities allow it to produce.

Large technology companies are already selling generative AI for software engineering, including GitHub Copilot, which is now integrated with OpenAI's GPT-4, and Replit, used by more than 20 million coders.[10]

How product R&D could be transformed

Early research analysis

Researchers use generative AI to enhance market reporting, ideation, and product or solution drafting.

Virtual design

Researchers use generative AI to generate prompt-based drafts and designs, allowing them to iterate quickly with more design options.

Virtual simulations

Researchers accelerate and optimize the virtual simulation phase if combined with new deep learning generative design techniques.

Physical test planning

Researchers optimize test cases for more efficient testing, reducing the time required for physical build and testing.

Product R&D
Generative AI's potential in R&D is perhaps less well recognized than its potential in other business functions. Still, our research indicates the technology could deliver productivity with a value ranging from 10 to 15 percent of overall R&D costs.

For example, the life sciences and chemical industries have begun using generative AI foundation models in their R&D for what is known as generative design. Foundation models can generate candidate molecules, accelerating the process of developing new drugs and materials. Entos, a biotech pharmaceutical company, has paired generative AI with automated synthetic development tools to design small-molecule therapeutics. But the same principles can be applied to the design of many other products, including larger-scale physical products and electrical circuits, among others.

While other generative design techniques have already unlocked some of the potential to apply AI in R&D, their cost and data requirements, such as the use of "traditional" machine learning, can limit their application. Pretrained foundation models that underpin generative AI, or models that have been enhanced with fine-tuning, have much broader areas of application than models optimized for a single task. They can therefore accelerate time to market and broaden the types of products to which generative design can be applied. For now, however, foundation models lack the capabilities to help design products across all industries.

In addition to the productivity gains that result from being able to quickly produce candidate designs, generative design can also enable improvements in the designs themselves, as in the following examples of the operational improvements generative AI could bring:

— **Enhanced design.** Generative AI can help product designers reduce costs by selecting and using materials more efficiently. It can also optimize designs for manufacturing, which can lead to cost reductions in logistics and production.

— **Improved product testing and quality.** Using generative AI in generative design can produce a higher-quality product, resulting in increased attractiveness and market appeal. Generative AI can help to reduce testing time of complex systems and accelerate trial phases involving customer testing through its ability to draft scenarios and profile testing candidates.

We also identified a new R&D use case for nongenerative AI: deep learning surrogates, the use of which has grown since our earlier research, can be paired with generative AI to produce even greater benefits (see Box 2, "Deep learning surrogates"). To be sure, integration will require the development of specific solutions, but the value could be significant because deep learning surrogates have the potential to accelerate the testing of designs proposed by generative AI.

While we have estimated the potential direct impacts of generative AI on the R&D function, we did not attempt to estimate the technology's potential to create entirely novel product categories. These are the types of innovations that can produce step changes not only in the performance of individual companies but in economic growth overall.

Box 2

Deep learning surrogates

Product design in industries producing physical products often involves physics-based virtual simulations such as computational fluid dynamics (CFD) and finite element analysis (FEA). Although they are faster than actual physical testing, these techniques can be time- and resource-intensive, especially for designing complex parts—running CFD simulations on graphics processing units can take hours. And these techniques are even more complex and compute-intensive when they involve simulations coupled across multiple disciplines (for example, physical stress and temperature distribution), which is sometimes called multiphysics.

Deep learning applications are now revolutionizing the virtual testing phase of the R&D process by using deep learning models to emulate (multi)physics-based simulations at higher speeds and lower costs. Instead of taking hours to run physics-based models, these deep learning surrogates can produce the results of simulations in just a few seconds, allowing researchers to test many more designs and enabling faster decision making on products and designs.

Value potential by modality

Technology has revolutionized the way we conduct business, and text-based AI is on the frontier of this change. Indeed, text-based data is plentiful, accessible, and easily processed and analyzed at large scale by LLMs, which has prompted a strong emphasis on them in the initial stages of generative AI development. The current investment landscape in generative AI is also heavily focused on text-based applications such as chatbots, virtual assistants, and language translation. However, we estimate that almost one-fifth of the value that generative AI can unlock across our use cases would take advantage of multimodal capabilities beyond text to text.

While most of generative AI's initial traction has been in text-based use cases, recent advances in generative AI have also led to breakthroughs in image generation, as OpenAI's DALL·E and Stable Diffusion have so amply illustrated, and much progress is being made in audio, including voice and music, and video. These capabilities have obvious applications in marketing for generating advertising materials and other marketing content, and these technologies are already being applied in media industries, including game design. Indeed, some of these examples challenge existing business models around talent, monetization, and intellectual property.[11]

The multimodal capabilities of generative AI could also be used effectively in R&D. Generative AI systems could create first drafts of circuit designs, architectural drawings, structural engineering designs, and thermal designs based on prompts that describe requirements for a product. Achieving this will require training foundation models in these domains (think of LLMs trained on "design languages"). Once trained, such foundation models could increase productivity on a similar magnitude to software development.

Value potential by industry

Across the 63 use cases we analyzed, generative AI has the potential to generate $2.6 trillion to $4.4 trillion in value across industries. Its precise impact will depend on a variety of factors, such as the mix and importance of different functions, as well as the scale of an industry's revenue (Exhibit 4).

Across 63 use cases, generative AI has the potential to generate $2.6 trillion to $4.4 trillion in value across industries.

Exhibit 4

Generative AI use cases will have different impacts on business functions across industries.

Generative AI productivity impact by business functions[1]

Low impact — High impact

	Total, % of industry revenue	**Total,** $ billion	Marketing and sales 760–1,200	Customer operations 340–470	Product and R&D 230–420	Software engineering 580–1,200	Supply chain and operations 280–530	Risk and legal 180–260	Strategy and finance 120–260	Corporate IT[2] 40–50	Talent and organization 60–90
Administrative and professional services	**0.9–1.4**	150–250									
Advanced electronics and semiconductors	**1.3–2.3**	100–170									
Advanced manufacturing[3]	**1.4–2.4**	170–290									
Agriculture	**0.6–1.0**	40–70									
Banking	**2.8–4.7**	200–340									
Basic materials	**0.7– 1.2**	120–200									
Chemical	**0.8–1.3**	80–140									
Construction	**0.7–1.2**	90–150									
Consumer packaged goods	**1.4–2.3**	160–270									
Education	**2.2–4.0**	120–230									
Energy	**1.0– 1.6**	150–240									
Healthcare	**1.8–3.2**	150–260									
High tech	**4.8–9.3**	240–460									
Insurance	**1.8– 2.8**	50–70									
Media and entertainment	**1.5– 2.6**	60–110									
Pharmaceuticals and medical products	**2.6–4.5**	60–110									
Public and social sector	**0.5–0.9**	70–110									
Real estate	**1.0–1.7**	110–180									
Retail[4]	**1.2–1.9**	240–390									
Telecommunications	**2.3–3.7**	60–100									
Travel, transport, and logistics	**1.2–2.0**	180–300									
		2,600–4,400									

Note: Figures may not sum to 100%, because of rounding.
[1]Excludes implementation costs (eg, training, licenses).
[2]Excluding software engineering.
[3]Includes aerospace, defense, and auto manufacturing.
[4]Including auto retail.
Source: Comparative Industry Service (CIS), IHS Markit; Oxford Economics; McKinsey Corporate and Business Functions database; McKinsey Manufacturing and Supply Chain 360; McKinsey Sales Navigator; Ignite, a McKinsey database; McKinsey analysis

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For example, our analysis estimates generative AI could contribute roughly $310 billion in additional value for the retail industry (including auto dealerships) by boosting performance in functions such as marketing and customer interactions. By comparison, the bulk of potential value in high tech comes from generative AI's ability to increase the speed and efficiency of software development (Exhibit 5).

Exhibit 5

Generative AI could deliver significant value when deployed in some use cases across a selection of top industries.

Selected examples of key use cases for main functional value drivers (nonexhaustive)

Value potential of function for the industry – High – Low

	Total value potential per industry, $ billion (% of industry revenue)	Value potential, as % of operating profits[1]	Product R&D, software engineering	Customer operations	Marketing and sales	Other functions
Banking	200–340 (3–5%)	9–15	**Legacy code conversion** Optimize migration of legacy frameworks with natural-language translation capabilities	**Customer emergency interactive voice response (IVR)** Partially automate, accelerate, and enhance resolution rate of customer emergencies through generative AI–enhanced IVR interactions (eg, for credit card losses)	**Custom retail banking offers** Push personalized marketing and sales content tailored for each client of the bank based on profile and history (eg, personalized nudges), and generate alternatives for A/B testing	**Risk model documentation** Create model documentation, and scan for missing documentation and relevant regulatory updates
Retail and consumer packaged goods[2]	400–660 (1–2%)	27–44	**Consumer research** Accelerate consumer research by testing scenarios, and enhance customer targeting by creating "synthetic customers" to practice with	**Augmented reality–assisted customer support** Rapidly inform the workforce in real time about the status of products and consumer preferences	**Assist copy writing for marketing content creation** Accelerate writing of copy for marketing content and advertising scripts	**Procurement suppliers process enhancement** Draft playbooks for negotiating with suppliers
Pharma and medical products	60–110 (3–5%)	15–25	**Research and drug discovery** Accelerate the selection of proteins and molecules best suited as candidates for new drug formulation	**Customer documentation generation** Draft medication instructions and risk notices for drug resale	**Generate content for commercial representatives** Prepare scripts for interactions with physicians	**Contract generation** Draft legal documents incorporating specific regulatory requirements

[1]Operating profit based on average profitability of selected industries in the 2020–22 period.
[2]Includes auto retail.

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In the banking industry, generative AI has the potential to improve on efficiencies already delivered by artificial intelligence by taking on lower-value tasks in risk management, such as required reporting, monitoring regulatory developments, and collecting data. In the life sciences industry, generative AI is poised to make significant contributions to drug discovery and development.

We share our detailed analysis of these industries in the following industry spotlights.

Generative AI could change the game for retail and consumer packaged goods companies

The technology could generate value for the retail and consumer packaged goods (CPG) industry by increasing productivity by 1.2 to 2.0 percent of annual revenues, or an additional $400 billion to $660 billion.[1] To streamline processes, generative AI could automate key functions such as customer service, marketing and sales, and inventory and supply chain management.

Technology has played an essential role in the retail and CPG industries for decades. Traditional AI and advanced-analytics solutions have helped companies manage vast pools of data across large numbers of SKUs, expansive supply chain and warehousing networks, and complex product categories such as consumables.

In addition, the industries are heavily customer facing, which offers opportunities for generative AI to complement previously existing artificial intelligence. For example, generative AI's ability to personalize offerings could optimize marketing and sales activities already handled by existing AI solutions. Similarly, generative AI tools excel at data management and could support existing AI-driven pricing tools. Applying generative AI to such activities could be a step toward integrating applications across a full enterprise.

Generative AI is already at work in some retail and CPG companies:

Reinvention of the customer interaction pattern
Consumers increasingly seek customization in everything from clothing and cosmetics to curated shopping experiences, personalized outreach, and food—and generative AI can improve that experience. Generative AI can aggregate market data to test concepts, ideas, and models. Stitch Fix, which uses algorithms to suggest style choices to its customers, has experimented with DALL·E to visualize products based on customer preferences regarding color, fabric, and style. Using text-to-image generation, the company's stylists can visualize an article of clothing based on a consumer's preferences and then identify a similar article among Stitch Fix's inventory.

Retailers can create applications that give shoppers a next-generation experience, creating a significant competitive advantage in an era when customers expect to have a single natural-language interface help them select products. For example, generative AI can improve the process of choosing and ordering ingredients for a meal or preparing food—imagine a chatbot that could pull up the most popular tips from the comments attached to a recipe. There is also a big opportunity to enhance customer value management by delivering personalized marketing campaigns through a chatbot. Such applications can have human-like conversations about products in ways that can increase customer satisfaction, traffic, and brand loyalty. Generative AI offers retailers and CPG companies many opportunities to cross-sell and upsell, collect insights to improve product offerings, and increase their customer base, revenue opportunities, and overall marketing ROI.

Accelerating the creation of value in key areas
Generative AI tools can facilitate copy writing for marketing and sales, help brainstorm creative marketing ideas, expedite consumer research, and accelerate content analysis and creation. The potential improvement in writing and visuals can increase awareness and improve sales conversion rates.

Rapid resolution and enhanced insights in customer care
The growth of e-commerce also elevates the importance of effective consumer interactions. Retailers can combine existing AI tools with generative AI to enhance the capabilities of chatbots, enabling them to better mimic the interaction style of human agents—for example, by responding directly to a customer's query, tracking or canceling an order, offering discounts, and upselling. Automating repetitive tasks allows human agents to devote more time to handling complicated customer problems and obtaining contextual information.

Disruptive and creative innovation
Generative AI tools can enhance the process of developing new versions of products by digitally creating new designs rapidly. A designer can generate packaging designs from scratch or generate variations on an existing design. This technology is developing rapidly and has the potential to add text-to-video generation.

Additional factors to consider

As retail and CPG executives explore how to integrate generative AI in their operations, they should keep in mind several factors that could affect their ability to capture value from the technology.

External inference. Generative AI has increased the need to understand whether generated content is based on fact or inference, requiring a new level of quality control.

Adversarial attacks. Foundation models are a prime target for attack by hackers and other bad actors, increasing the variety of potential security vulnerabilities and privacy risks.

To address these concerns, retail and CPG companies will need to strategically keep humans in the loop and ensure security and privacy are top considerations for any implementation. Companies will need to institute new quality checks for processes previously handled by humans, such as emails written by customer reps, and perform more-detailed quality checks on AI-assisted processes such as product design.

1 Vehicular retail is included as part of our overall retail analysis.

Banks could realize substantial value from generative AI

Generative AI could have a significant impact on the banking industry, generating value from increased productivity of 2.8 to 4.7 percent of the industry's annual revenues, or an additional $200 billion to $340 billion. On top of that impact, the use of generative AI tools could also enhance customer satisfaction, improve decision making and employee experience, and decrease risks through better monitoring of fraud and risk.

Banking, a knowledge and technology-enabled industry, has already benefited significantly from previously existing applications of artificial intelligence in areas such as marketing and customer operations.[1] Generative AI applications could deliver additional benefits, especially because text modalities are prevalent in areas such as regulations and programming language, and the industry is customer facing, with many B2C and small-business customers.[2]

Several characteristics position the industry for the integration of generative AI applications:

— *Sustained digitization efforts along with legacy IT systems.* Banks have been investing in technology for decades, accumulating a significant amount of technical debt along with a siloed and complex IT architecture.[3]

— *Large customer-facing workforces.* Banking relies on a large number of service representatives such as call-center agents and wealth management financial advisers.

— *A stringent regulatory environment.* As a heavily regulated industry, banking has a substantial number of risk, compliance, and legal needs.

— *White-collar industry.* Generative AI's impact could span the organization, assisting all employees in writing emails, creating business presentations, and other tasks.

On the move

Banks have started to grasp the potential of generative AI in their front lines and in their software activities. Early adopters are harnessing solutions such as ChatGPT as well as industry-specific solutions, primarily for software and knowledge applications. Three uses demonstrate its value potential to the industry:

A virtual expert to augment employee performance
A generative AI bot trained on proprietary knowledge such as policies, research, and customer interaction could provide always-on, deep technical support. Today, frontline spending is dedicated mostly to validating offers and interacting with clients, but giving frontline workers access to data as well could improve the customer experience. The technology could also monitor industries and clients and send alerts on semantic queries from public sources. For example, Morgan Stanley is building an AI assistant using GPT-4, with the aim of helping tens of thousands of wealth managers quickly find and synthesize answers from a massive internal knowledge base.[4] The model combines search and content creation so wealth managers can find and tailor information for any client at any moment.

One European bank has leveraged generative AI to develop an environmental, social, and governance (ESG) virtual expert by synthesizing and extracting from long documents with unstructured information. The model answers complex questions based on a prompt, identifying the source of each answer and extracting information from pictures and tables.

Generative AI could reduce the significant costs associated with back-office operations. Such customer-facing chatbots could assess user requests and select the best service expert to address them based on characteristics such as topic, level of difficulty, and type of customer. Through generative AI assistants, service professionals could rapidly access all relevant information such as product guides and policies to instantaneously address customer requests.

Code acceleration to reduce tech debt and deliver software faster
Generative AI tools are useful for software development in four broad categories. First, they can draft code based on context via input code or natural language, helping developers code more quickly and with reduced friction while enabling automatic translations and no- and low-code tools. Second, such tools can automatically generate, prioritize, run, and review different code tests, accelerating testing and increasing coverage and effectiveness. Third, generative AI's natural-language translation capabilities can optimize the integration and migration of legacy frameworks. Last, the tools can review code to identify defects and inefficiencies in computing. The result is more robust, effective code.

1 "Building the AI bank of the future," McKinsey, May 2021.
2 *McKinsey's Global Banking Annual Review*, December 1, 2022.
3 Akhil Babbar, Raghavan Janardhanan, Remy Paternoster, and Henning Soller, "Why most digital banking transformations fail—and how to flip the odds," McKinsey, April 11, 2023.
4 Hugh Son, "Morgan Stanley is testing an OpenAI-powered chatbot for its 16,000 financial advisors," CNBC, March 14, 2023.

Production of tailored content at scale
Generative AI tools can draw on existing documents and data sets to substantially streamline content generation. These tools can create personalized marketing and sales content tailored to specific client profiles and histories as well as a multitude of alternatives for A/B testing. In addition, generative AI could automatically produce model documentation, identify missing documentation, and scan relevant regulatory updates to create alerts for relevant shifts.

Factors for banks to consider

When exploring how to integrate generative AI into operations, banks can be mindful of a number of factors:

— *The level of regulation for different processes.* These vary from unregulated processes such as customer service to heavily regulated processes such as credit risk scoring.

— *Type of end user.* End users vary widely in their expectations and familiarity with generative AI—for example, employees compared with high-net-worth clients.

— *Intended level of work automation.* AI agents integrated through APIs could act nearly autonomously or as copilots, giving real-time suggestions to agents during customer interactions.

— *Data constraints.* While public data such as annual reports could be made widely available, there would need to be limits on identifiable details for customers and other internal data.

A generative AI bot trained on proprietary knowledge such as policies, research, and customer interaction could provide always-on, deep technical support.

Generative AI deployment could unlock potential value equal to 2.6 to 4.5 percent of annual revenues across the pharmaceutical and medical-product industries

Our analysis finds that generative AI could have a significant impact on the pharmaceutical and medical-product industries—from $60 billion to $110 billion annually. This big potential reflects the resource-intensive process of discovering new drug compounds. Pharma companies typically spend approximately 20 percent of revenues on R&D,[1] and the development of a new drug takes an average of ten to 15 years.

With this level of spending and timeline, improving the speed and quality of R&D can generate substantial value. For example, lead identification—a step in the drug discovery process in which researchers identify a molecule that would best address the target for a potential new drug—can take several months even with "traditional" deep learning techniques. Foundation models and generative AI can enable organizations to complete this step in a matter of weeks.

Generative AI use cases aligned to industry needs

Drug discovery involves narrowing the universe of possible compounds to those that could effectively treat specific conditions. Generative AI's ability to process massive amounts of data and model options can accelerate output across several use cases:

Improve automation of preliminary screening

In the lead identification stage of drug development, scientists can use foundation models to automate the preliminary screening of chemicals in the search for those that will produce specific effects on drug targets. To start, thousands of cell cultures are tested and paired with images of the corresponding experiment. Using an off-the-shelf foundation model, researchers can cluster similar images more precisely than they can with traditional models, enabling them to select the most promising chemicals for further analysis during lead optimization.

Enhance indication finding

An important phase of drug discovery involves the identification and prioritization of new indications—that is, diseases, symptoms, or circumstances that justify the use of a specific medication or other treatment, such as a test, procedure, or surgery. Possible indications for a given drug are based on a patient group's clinical history and medical records, and they are then prioritized based on their similarities to established and evidence-backed indications.

Researchers start by mapping the patient cohort's clinical events and medical histories—including potential diagnoses, prescribed medications, and performed procedures—from real-world data. Using foundation models, researchers can quantify clinical events, establish relationships, and measure the similarity between the patient cohort and evidence-backed indications. The result is a short list of indications that have a better probability of success in clinical trials because they can be more accurately matched to appropriate patient groups.

Pharma companies that have used this approach have reported high success rates in clinical trials for the top five indications recommended by a foundation model for a tested drug. This success has allowed these drugs to progress smoothly into Phase 3 trials, significantly accelerating the drug development process.

Additional factors to consider

Before integrating generative AI into operations, pharma executives should be aware of some factors that could limit their ability to capture its benefits:

— *The need for a human in the loop.* Companies may need to implement new quality checks on processes that shift from humans to generative AI, such as representative-generated emails, or more detailed quality checks on AI-assisted processes, such as drug discovery. The increasing need to verify whether generated content is based on fact or inference elevates the need for a new level of quality control.

— *Explainability.* A lack of transparency into the origins of generated content and traceability of root data could make it difficult to update models and scan them for potential risks; for instance, a generative AI solution for synthesizing scientific literature may not be able to point to the specific articles or quotes that led it to infer that a new treatment is very popular among physicians. The technology can also "hallucinate," or generate responses that are obviously incorrect or inappropriate for the context. Systems need to be designed to point to specific articles or data sources, and then do human-in-the-loop checking.

— *Privacy considerations.* Generative AI's use of clinical images and medical records could increase the risk that protected health information will leak, potentially violating regulations that require pharma companies to protect patient privacy.

[1] *Research and development in the pharmaceutical industry*, Congressional Budget Office, April 2021.

In this chapter, we have estimated the organizational value generative AI could deliver through use cases across industries and business functions, but the technology's potential is much greater. As it is embedded into tools used by every knowledge worker, its additional impact may be more diffuse but no less valuable than that associated with these use cases. Companies need to find ways to maximize the value created by the generative AI they deploy while also taking care to monitor and manage its impact on their workforces and society at large.

The generative AI future of work: Impacts on work activities, economic growth, and productivity

Technology has been changing the anatomy of work for decades. Over the years, machines have given human workers various “superpowers”; for instance, industrial-age machines enabled workers to accomplish physical tasks beyond the capabilities of their own bodies. More recently, computers have enabled knowledge workers to perform calculations that would have taken years to do manually.

These examples illustrate how technology can augment work through the automation of individual activities that workers would have otherwise had to do themselves. At a conceptual level, the application of generative AI may follow the same pattern in the modern workplace, although as we show later in this chapter, the types of activities that generative AI could affect, and the types of occupations with activities that could change, will likely be different as a result of this technology than for older technologies.

The McKinsey Global Institute began analyzing the impact of technological automation of work activities and modeling scenarios of adoption in 2017. At that time, we estimated that workers spent half of their time on activities that had the potential to be automated by adapting technology that existed at that time, or what we call technical automation potential. We also modeled a range of potential scenarios for the pace at which these technologies could be adopted and affect work activities throughout the global economy.

Technology adoption at scale does not occur overnight. The potential of technological capabilities in a lab does not necessarily mean they can be immediately integrated into a solution that automates a specific work activity—developing such solutions takes time. Even when such a solution is developed, it might not be economically feasible to use if its costs exceed those of human labor. Additionally, even if economic incentives for deployment exist, it takes time for adoption to spread across the global economy. Hence, our adoption scenarios, which consider these factors together with the technical automation potential, provide a sense of the pace and scale at which workers' activities could shift over time.

Large-scale shifts in the mix of work activities and occupations are not unprecedented. Consider the work of a farmer today compared with what a farmer did just a few short years ago. Many farmers now access market information on mobile phones to determine when and where to sell their crops or download sophisticated modeling of weather patterns. From a more macro perspective, agricultural employment in China went from an 82 percent share of all workers in 1962 to 13 percent in 2013. Labor markets are also dynamic: millions of people leave their jobs every month in the United States.[12] But this does not minimize the challenges faced by individual workers whose lives are upended by these shifts, or the organizational or societal challenges of ensuring that workers have the skills to take on the work that will be in demand and that their incomes are sufficient to grow their standards of living.

Also, demographics have made such shifts in activities a necessity from a macroeconomic perspective. An economic growth gap has opened as a result of the slowing growth of the world's workforce. In some major countries, workforces have shrunk because populations are aging. Labor productivity will have to accelerate to achieve economic growth and enhance prosperity.

The analyses in this paper incorporate the potential impact of generative AI on today's work activities. The new capabilities of generative AI, combined with previous technologies and integrated into corporate operations around the world, could accelerate the potential for technical automation of individual activities and the adoption of technologies that augment the capabilities of the workforce. They could also have an impact on knowledge workers whose activities were not expected to shift as a result of these technologies until later in the future (see Box 3, "About the research").

Labor productivity will have to accelerate to achieve economic growth and enhance prosperity.

Box 3

About the research

This analysis builds on the methodology we established in 2017. We began by examining the US Bureau of Labor Statistics O*Net breakdown of about 850 occupations into roughly 2,100 detailed work activities. For each of these activities, we scored the level of capability necessary to successfully perform the activity against a set of 18 capabilities that have the potential for automation (exhibit).

We also surveyed experts in the automation of each of these capabilities to estimate automation technologies' current performance level against each of these capabilities, as well as how the technology's performance might advance over time. Specifically, this year, we updated our assessments of technology's performance in cognitive, language, and social and emotional capabilities based on a survey of generative AI experts.

Based on these assessments of the technical automation potential of each detailed work activity at each point in time, we modeled potential scenarios for the adoption of work automation around the world. First, we estimated a range of time to implement a solution that could automate each specific detailed work activity, once all the capability requirements were met by the state of technology development. Second, we estimated a range of potential costs for this technology when it is first introduced, and then declining over time, based on historical precedents. We modeled the beginning of adoption for a specific detailed work activity in a particular occupation in a country (for 47 countries, accounting for more than 80 percent of the global workforce) when the cost of the automation technology reaches parity with the cost of human labor in that occupation.

Based on a historical analysis of various technologies, we modeled a range of adoption timelines from eight to 27 years between the beginning of adoption and its plateau, using sigmoidal curves (S-curves). This range implicitly accounts for the many factors that could affect the pace at which adoption occurs, including regulation, levels of investment, and management decision making within firms.

The modeled scenarios create a time range for the potential pace of automating current work activities. The "earliest" scenario flexes all parameters to the extremes of plausible assumptions, resulting in faster automation development and adoption, and the "latest" scenario flexes all parameters in the opposite direction. The reality is likely to fall somewhere between the two.

Exhibit

Our analysis assesses the potential for technical automation across some 2,100 activities and 18 capabilities.

~850 occupations

Examples

- **Retail salespeople**
- Health practitioners
- Food and beverage service workers
- Teachers

~2,100 activities assessed across all occupations

Example: Retail activities

- Answer questions about products and services
- Greet customers
- Clean and maintain work areas
- Demonstrate product features
- Process sales and transactions

Capability requirements

Sensory
- Sensory perception

Cognitive
- Retrieving information
- Recognizing known patterns and categories (supervised learning)
- Generating novel patterns and categories
- Logical reasoning and problem solving
- Optimizing and planning
- Creativity
- Articulating/display output
- Coordination with multiple agents

Physical
- Fine motor skills and dexterity
- Gross motor skills
- Navigation
- Mobility

Natural-language processing
- Understanding natural language
- Generating natural language

Social
- Social and emotional sensing
- Social and emotional reasoning
- Social and emotional output

Source: McKinsey Global Institute analysis

McKinsey & Company

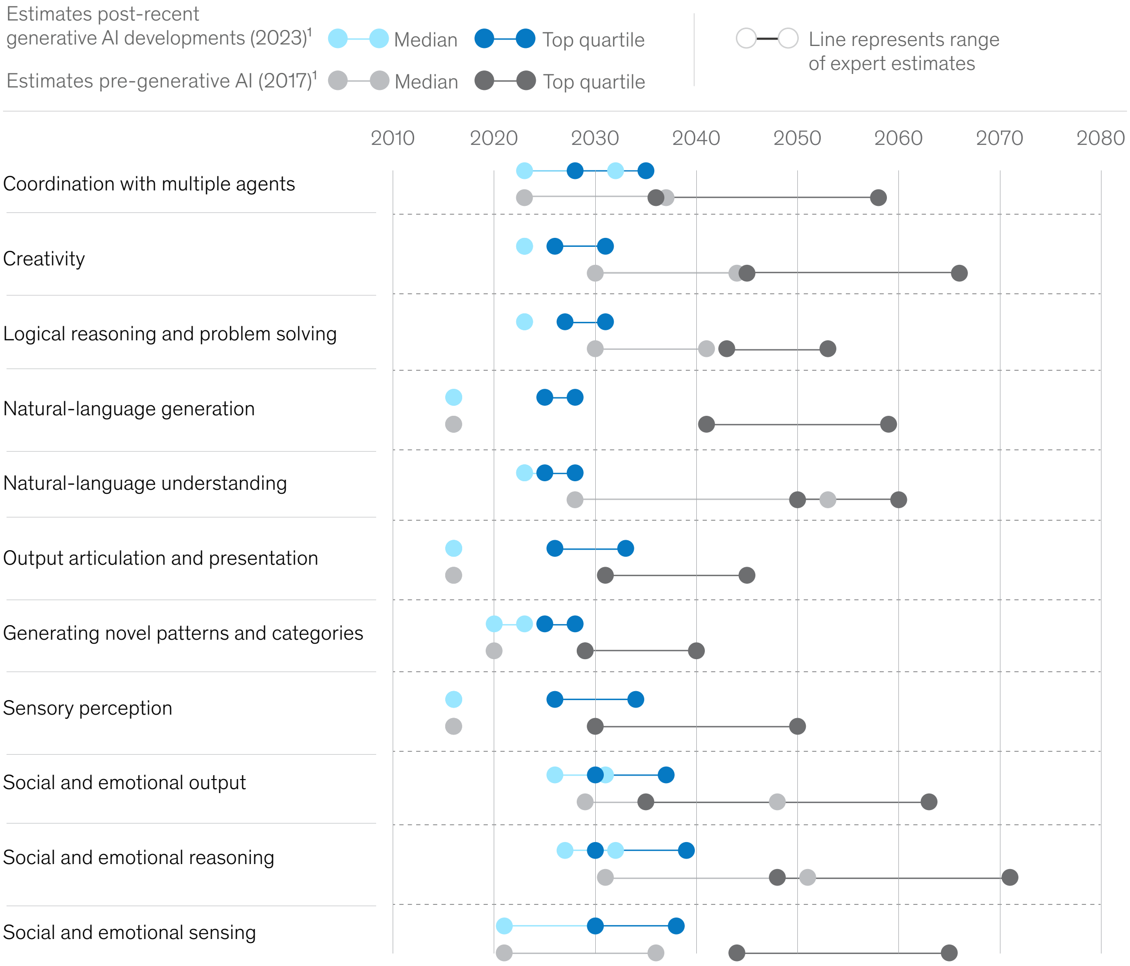
Accelerating the technical potential to transform knowledge work

Based on developments in generative AI, technology performance is now expected to match median human performance and reach top quartile human performance earlier than previously estimated across a wide range of capabilities (Exhibit 6). For example, MGI previously identified 2027 as the earliest year when median human performance for natural-language understanding might be achieved in technology, but in this new analysis, the corresponding point is 2023.

Exhibit 6

As a result of generative AI, experts assess that technology could achieve human-level performance in some technical capabilities sooner than previously thought.

Technical capabilities, level of human performance achievable by technology



[1]Comparison made on the business-related tasks required from human workers. Please refer to technical appendix for detailed view of performance rating methodology.
Source: McKinsey Global Institute occupation database; McKinsey analysis

McKinsey & Company

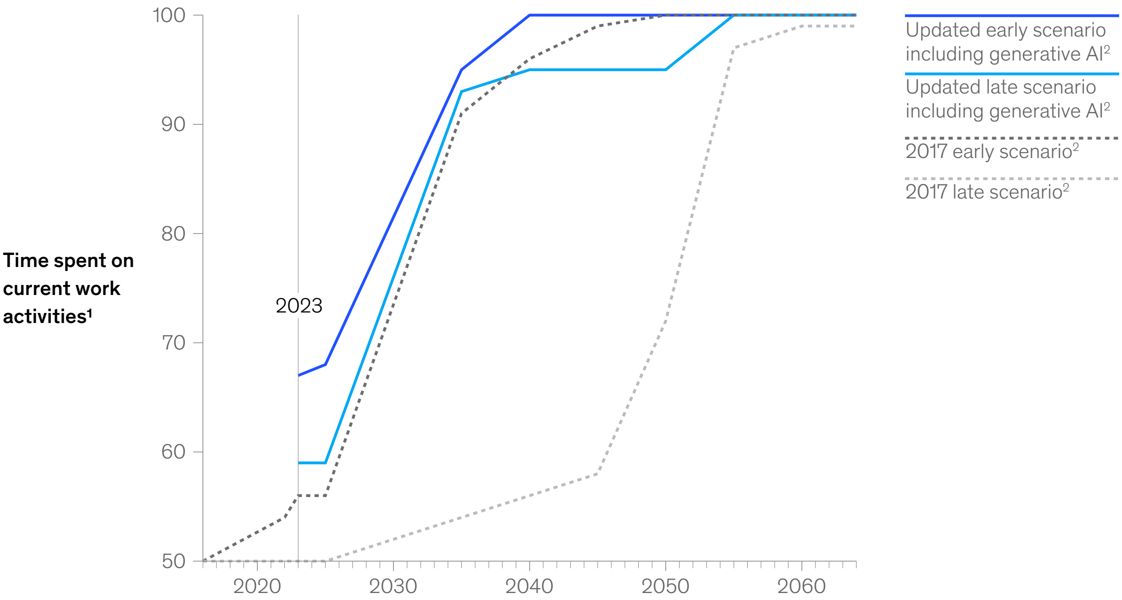
As a result of these reassessments of technology capabilities due to generative AI, the total percentage of hours that could theoretically be automated by integrating technologies that exist today has increased from about 50 percent to 60–70 percent. The technical potential curve is quite steep because of the acceleration in generative AI's natural-language capabilities (Exhibit 7).

Interestingly, the range of times between the early and late scenarios has compressed compared with the expert assessments in 2017, reflecting a greater confidence that higher levels of technological capabilities will arrive by certain time periods.

Exhibit 7

The advent of generative AI has pulled forward the potential for technical automation.

Technical automation potentials by scenario, %



[1]Includes data from 47 countries, representing about 80% of employment across the world. 2017 estimates are based on the activity and occupation mix from 2016. Scenarios including generative AI are based on the 2021 activity and occupation mix.
[2]Early and late scenarios reflect the ranges provided by experts (see Exhibit 6).
Source: McKinsey Global Institute analysis

McKinsey & Company

Adoption lags behind technical automation potential

Our analysis of adoption scenarios accounts for the time required to integrate technological capabilities into solutions that can automate individual work activities; the cost of these technologies compared with that of human labor in different occupations and countries around the world; and the time it has taken for technologies to diffuse across the economy. With the acceleration in technical automation potential that generative AI enables, our scenarios for automation adoption have correspondingly accelerated. These scenarios encompass a wide range of outcomes, given that the pace at which solutions will be developed and adopted will vary based on decisions that will be made on investments, deployment, and regulation, among other factors. But they give an indication of the degree to which the activities that workers do each day may shift.

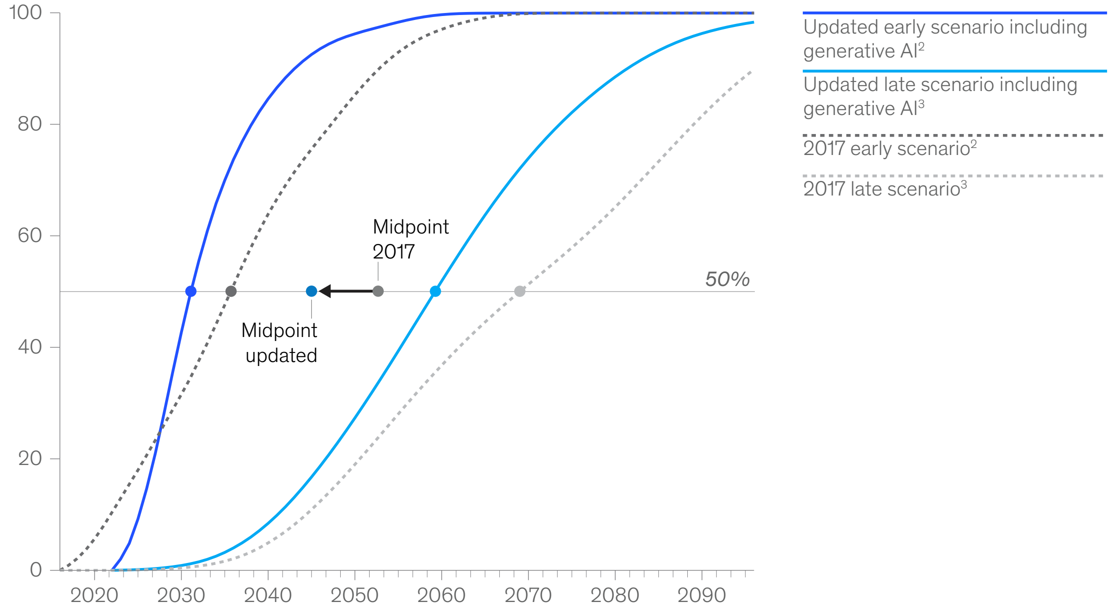
As an example of how this might play out in a specific occupation, consider postsecondary English language and literature teachers, whose detailed work activities include preparing tests and evaluating student work. With generative AI's enhanced natural-language capabilities, more of these activities could be done by machines, perhaps initially to create a first draft that is edited by teachers but perhaps eventually with far less human editing required. This could free up time for these teachers to spend more time on other work activities, such as guiding class discussions or tutoring students who need extra assistance.

Our previously modeled adoption scenarios suggested that 50 percent of time spent on 2016 work activities would be automated sometime between 2035 and 2070, with a midpoint scenario around 2053. Our updated adoption scenarios, which account for developments in generative AI, models the time spent on 2023 work activities reaching 50 percent automation between 2030 and 2060, with a midpoint of 2045—an acceleration of roughly a decade compared with the previous estimate (Exhibit 8).[13]

Exhibit 8

The midpoint scenario at which automation adoption could reach 50 percent of time spent on current work activities has accelerated by a decade.

Global automation of time spent on current work activities,[1] %



[1]Includes data from 47 countries, representing about 80% of employment across the world. 2017 estimates are based on the activity and occupation mix from 2016. Scenarios including generative AI are based on the 2021 activity and occupation mix.
[2]Early scenario: aggressive scenario for all key model parameters (technical automation potential, integration timelines, economic feasibility, and technology diffusion rates.).
[3]Late scenario: parameters are set for later adoption potential.
Source: McKinsey Global Institute analysis

McKinsey & Company

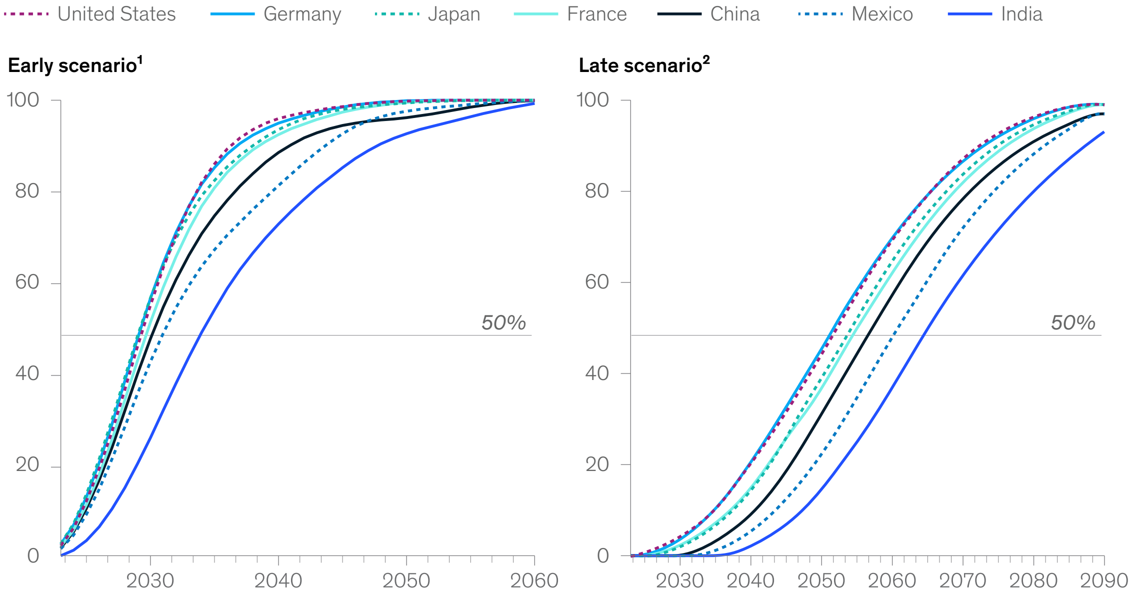
Different countries, different pace of adoption

Adoption is also likely to be faster in developed countries, where wages are higher and thus the economic feasibility of adopting automation occurs earlier. Even if the potential for technology to automate a particular work activity is high, the costs required to do so have to be compared with the cost of human wages. In countries such as China, India, and Mexico, where wage rates are lower, automation adoption is modeled to arrive more slowly than in higher-wage countries (Exhibit 9).

Exhibit 9

Automation adoption is likely to be faster in developed economies, where higher wages will make it economically feasible sooner.

Automation adoption by scenario for select countries, %



[1]Early scenario: aggressive scenario for all key model parameters (technical automation potential, integration timelines, economic feasibility, and technology diffusion rates.).
[2]Late scenario: parameters are set for the later adoption potential.
Source: McKinsey Global Institute analysis

McKinsey & Company

Our analyses of generative AI's impact on work activities and the pace of automation adoption rely on several assumptions and sensitivities (see Box 4, "Limitations of our analyses, key assumptions, and sensitivities").

Box 4

Limitations of our analyses, key assumptions, and sensitivities

This analysis considers the potential for automation only of current work activities and occupations. It does not account for how those work activities may shift over time or forecast new activities and occupations.[1] Also, the analysis accounts solely for first-order effects. It does not take into account how labor rates could change, and it does not model changes in labor force participation rates or other general equilibrium effects. That said, while these models account for the time it may take for technology to be adopted across an economy, technologies could be adopted much more rapidly in an individual organization. Other research may reach different conclusions.

Our assessments of technology capabilities are based on the best estimates of experts involved in developing automation technologies. These assessments could change over time, as they have changed since 2017.

The technology adoption curves are based on historical findings that technologies take eight to 27 years from commercial availability to reach a plateau in adoption. Some argue that the adoption of generative AI will be faster due to the ease of deploying these technologies. That said, the case for a minimum of eight years in our earliest scenario for reaching a global plateau in adoption accounts for the pace of adoption of other technologies that have arguably had a faster adoption potential—for example, social networking as a consumer technology that faced no barriers in enterprise change management. Our scenario also accounts for the significant role of small and midsize enterprises around the world, in addition to the challenges of incorporating and managing change in larger organizations.

In addition, this analysis does not assume that the scale of work automation equates directly to job losses. Like other technologies, generative AI typically enables individual activities within occupations to be automated, not entire occupations. Historically, the activities in many occupations have shifted over time as certain activities are automated. However, organizations may decide to realize the benefits of increased productivity by reducing employment in some job categories, a possibility we cannot rule out.

1 David Autor et al., *New frontiers: The origins and content of new work*, 1940–2018, National Bureau of Economic Research working paper number 30389, August 2022; Jeffrey Lin, “Technological adaptation, cities, and new work,” *Review of Economics and Statistics*, May 2011, Volume 93, Number 2.

Generative AI is likely to have the biggest impact on knowledge work, particularly activities involving decision making and collaboration, which previously had the lowest potential for automation.

Generative AI's potential impact on knowledge work

Previous generations of automation technology were particularly effective at automating data management tasks related to collecting and processing data. Generative AI's natural-language capabilities increase the automation potential of these types of activities somewhat. But its impact on more physical work activities shifted much less, which isn't surprising because its capabilities are fundamentally engineered to do cognitive tasks.

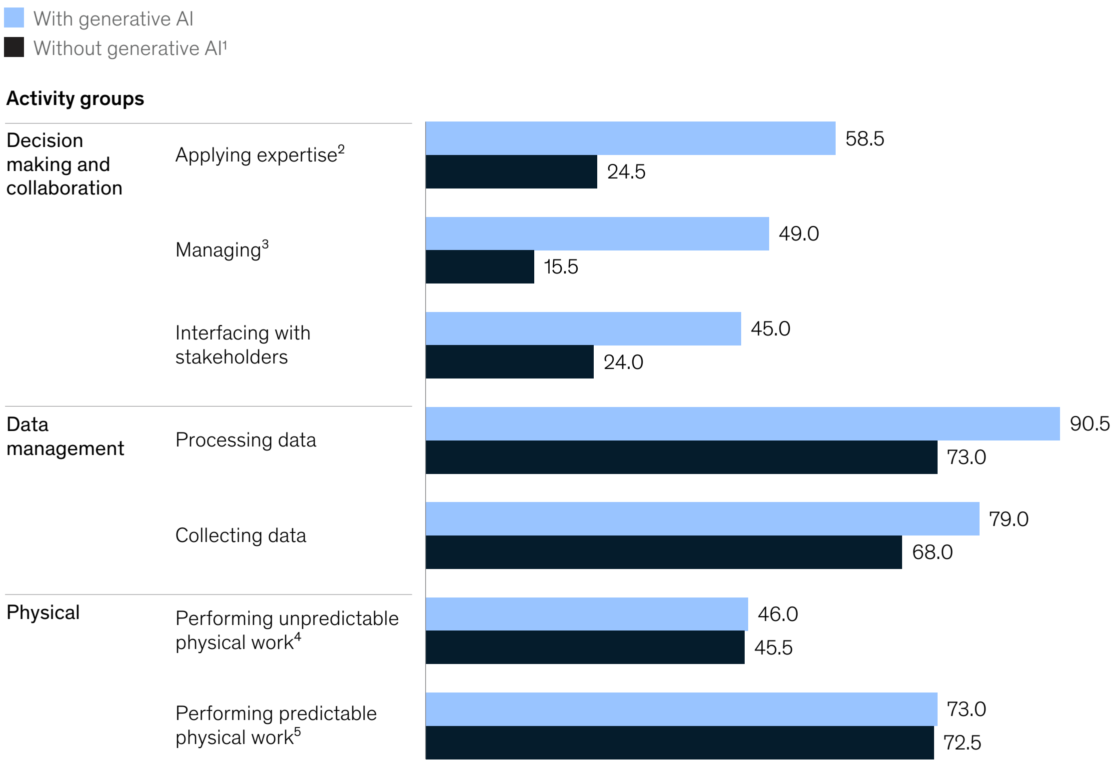
As a result, generative AI is likely to have the biggest impact on knowledge work, particularly activities involving decision making and collaboration, which previously had the lowest potential for automation (Exhibit 10). Our estimate of the technical potential to automate the application of expertise jumped 34 percentage points, while the potential to automate management and develop talent increased from 16 percent in 2017 to 49 percent in 2023.

Generative AI's ability to understand and use natural language for a variety of activities and tasks largely explains why automation potential has risen so steeply. Some 40 percent of the activities that workers perform in the economy require at least a median level of human understanding of natural language.

Exhibit 10

Generative AI could have the biggest impact on collaboration and the application of expertise, activities that previously had a lower potential for automation.

Overall technical automation potential, comparison in midpoint scenarios, % in 2023



Note: Figures may not sum, because of rounding.
[1]Previous assessment of work automation before the rise of generative AI.
[2]Applying expertise to decision making, planning, and creative tasks.
[3]Managing and developing people.
[4]Performing physical activities and operating machinery in unpredictable environments.
[5]Performing physical activities and operating machinery in predictable environments.
Source: McKinsey Global Institute analysis

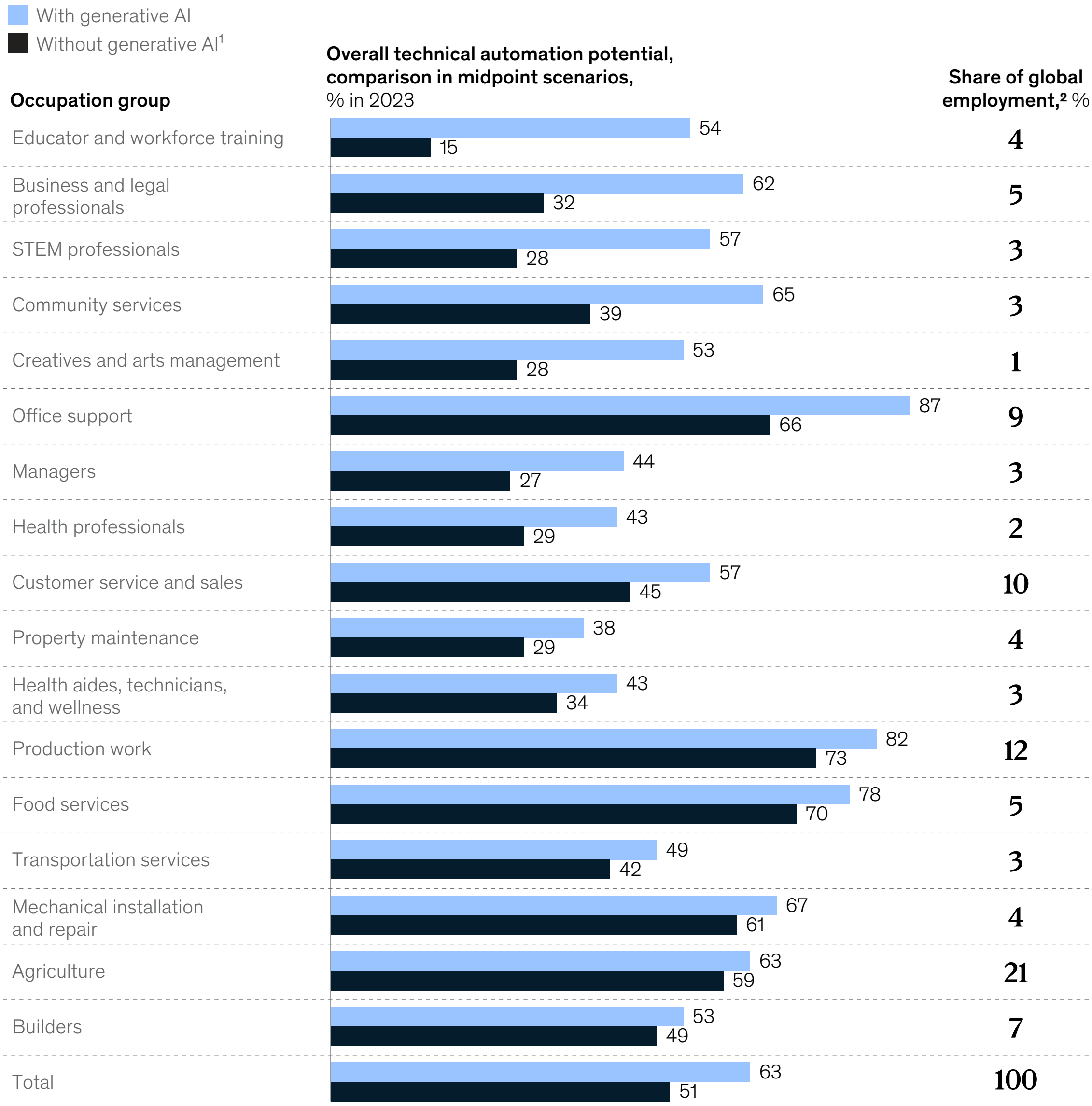
McKinsey & Company

As a result, many of the work activities that involve communication, supervision, documentation, and interacting with people in general have the potential to be automated by generative AI, accelerating the transformation of work in occupations such as education and technology, for which automation potential was previously expected to emerge later (Exhibit 11).

Exhibit 11

Advances in technical capabilities could have the most impact on activities performed by educators, professionals, and creatives.

Impact of generative AI on technical automation potential in midpoint scenario, 2023



Note: Figures may not sum, because of rounding.
[1]Previous assessment of work automation before the rise of generative AI.
[2]Includes data from 47 countries, representing about 80% of employment across the world.
Source: McKinsey Global Institute analysis

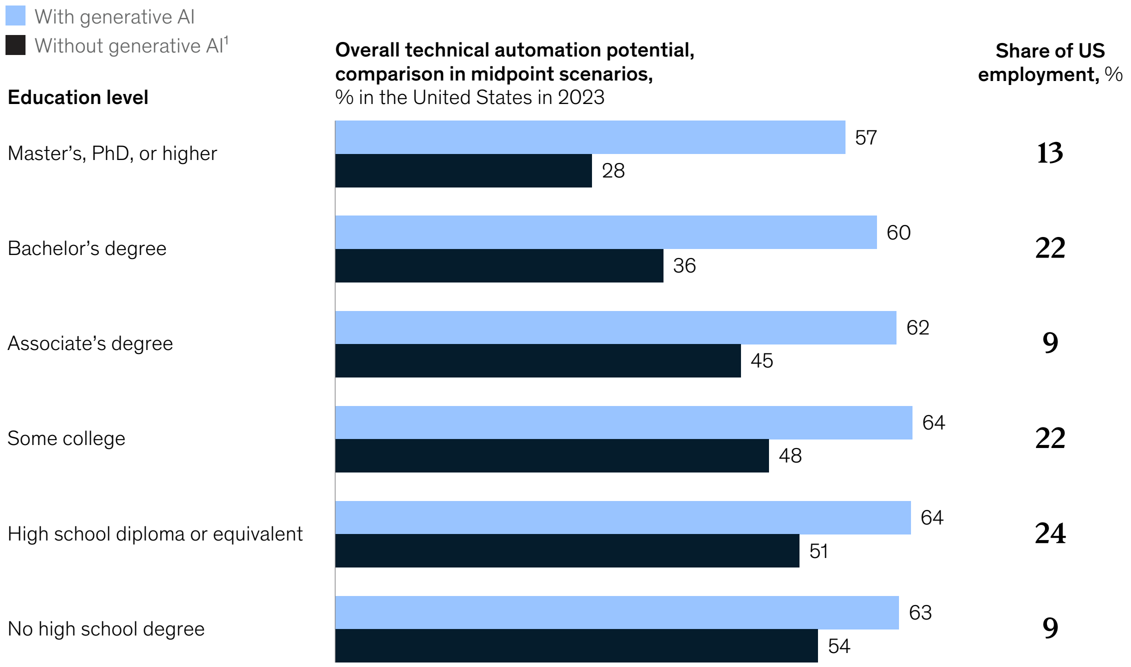
McKinsey & Company

Labor economists have often noted that the deployment of automation technologies tends to have the most impact on workers with the lowest skill levels, as measured by educational attainment, or what is called skill biased. We find that generative AI has the opposite pattern—it is likely to have the most incremental impact through automating some of the activities of more-educated workers (Exhibit 12).

Exhibit 12

Generative AI increases the potential for technical automation most in occupations requiring higher levels of educational attainment.

Impact of generative AI on technical automation potential in midpoint scenario, 2023



[1]Previous assessment of work automation before the rise of generative AI.
Source: McKinsey Global Institute analysis

McKinsey & Company

Another way to interpret this result is that generative AI will challenge the attainment of multiyear degree credentials as an indicator of skills, and others have advocated for taking a more skills-based approach to workforce development in order to create more equitable, efficient workforce training and matching systems.[14] Generative AI could still be described as skill-biased technological change, but with a different, perhaps more granular, description of skills that are more likely to be replaced than complemented by the activities that machines can do.

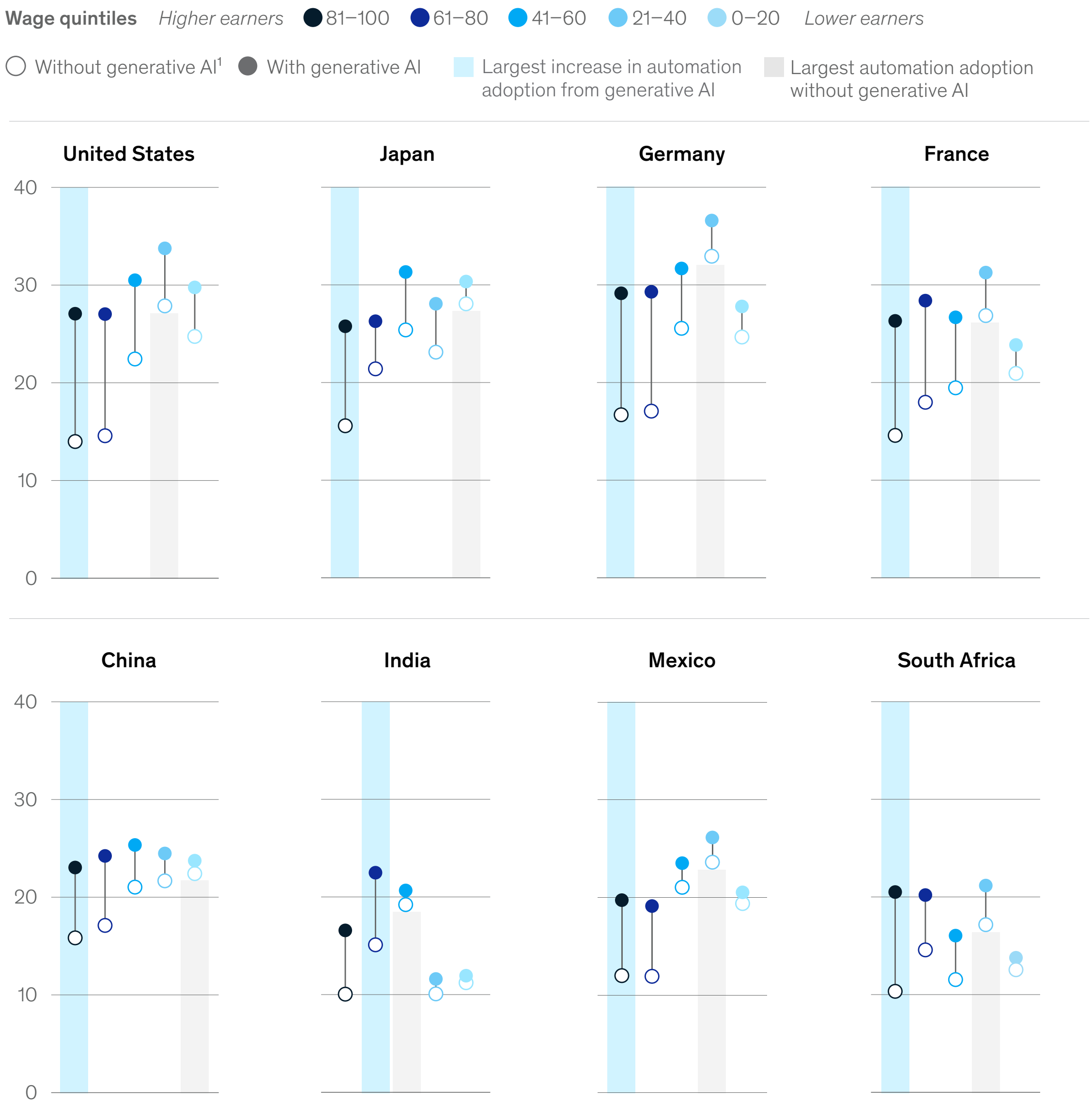
Previous generations of automation technology often had the most impact on occupations with wages falling in the middle of the income distribution. For lower-wage occupations, making a case for work automation is more difficult because the potential benefits of automation compete against a lower cost of human labor. Additionally, some of the tasks performed in lower-wage occupations are technically difficult to automate—for example, manipulating fabric or picking delicate fruits. Some labor economists have observed a “hollowing out of the middle,” and our previous models have suggested that work automation would likely have the biggest midterm impact on lower-middle-income quintiles.

However, generative AI’s impact is likely to most transform the work of higher-wage knowledge workers because of advances in the technical automation potential of their activities, which were previously considered to be relatively immune from automation (Exhibit 13).

Exhibit 13

Generative AI could have the biggest impact on activities in high-wage jobs; previously, automation’s impact was highest in lower-middle-income quintiles.

Automation adoption per wage quintile, % in 2030, midpoint scenario



[1]Previous assessment of work automation before the rise of generative AI.
Source: McKinsey Global Institute analysis

McKinsey & Company

Generative AI could propel higher productivity growth

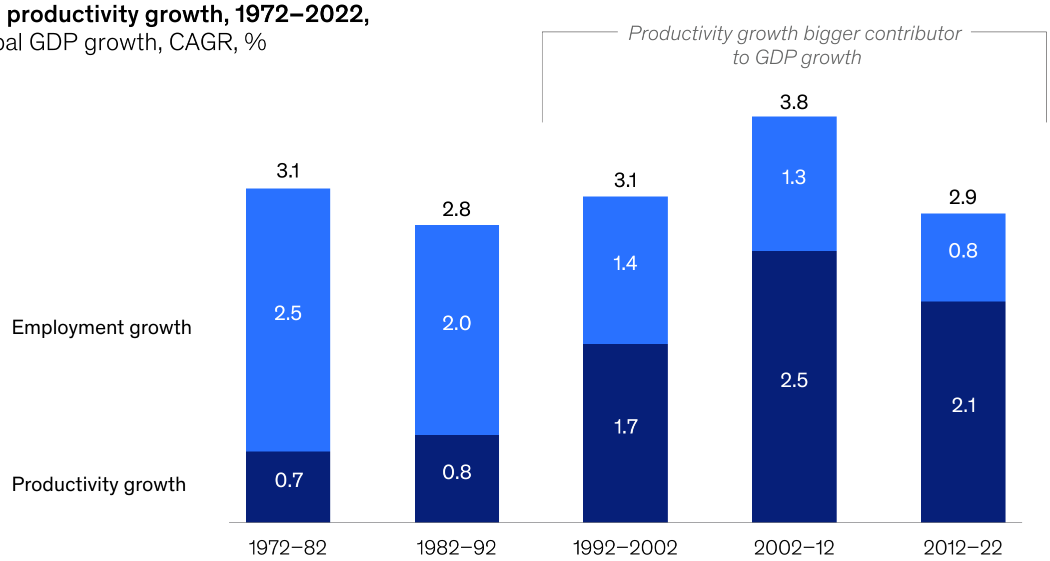
Global economic growth was slower from 2012 to 2022 than in the two preceding decades.[15] Although the COVID-19 pandemic was a significant factor, long-term structural challenges—including declining birth rates and aging populations—are ongoing obstacles to growth.

Declining employment is among those obstacles. Compound annual growth in the total number of workers worldwide slowed from 2.5 percent in 1972–82 to just 0.8 percent in 2012–22, largely because of aging. In many large countries, the size of the workforce is already declining.[16] Productivity, which measures output relative to input, or the value of goods and services produced divided by the amount of labor, capital, and other resources required to produce them, was the main engine of economic growth in the three decades from 1992 to 2022 (Exhibit 14). However, since then, productivity growth has slowed in tandem with slowing employment growth, confounding economists and policy makers.[17]

Exhibit 14

Productivity growth, the main engine of GDP growth over the past 30 years, slowed down in the past decade.

Real GDP growth contribution of employment and productivity growth, 1972–2022,
global GDP growth, CAGR, %



Source: Conference Board Total Economy database; McKinsey Global Institute analysis

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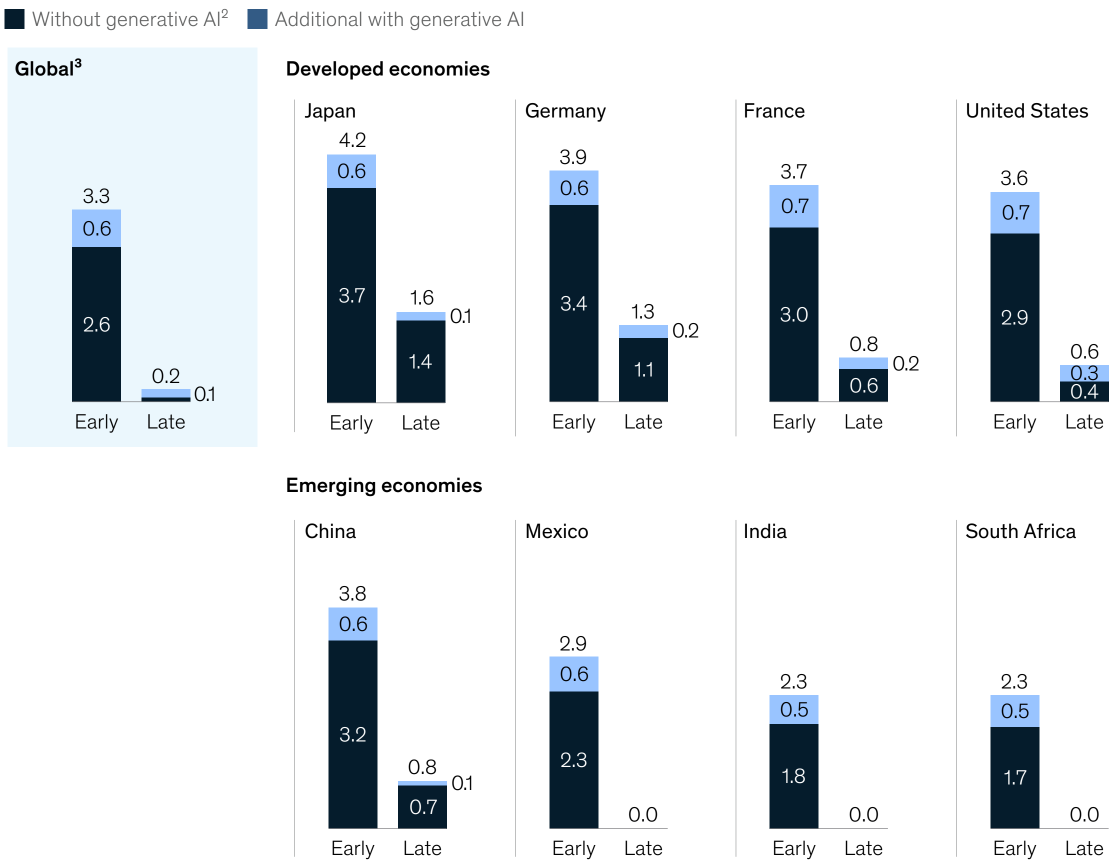
The deployment of generative AI and other technologies could help accelerate productivity growth, partially compensating for declining employment growth and enabling overall economic growth. Based on our estimates, the automation of individual work activities enabled by these technologies could provide the global economy with an annual productivity boost of 0.2 to 3.3 percent from 2023 to 2040 depending on the rate of automation adoption—with generative AI contributing to 0.1 to 0.6 percentage points of that growth—but only if individuals affected by the technology were to shift to other work activities that at least match their 2022 productivity levels (Exhibit 15). In some cases, workers will stay in the same occupations, but their mix of activities will shift; in others, workers will need to shift occupations.

Exhibit 15

Generative AI could contribute to productivity growth if labor hours can be redeployed effectively.

Productivity impact from automation by scenario, 2022–40, CAGR,[1] %



Note: Figures may not sum, because of rounding.
[1]Based on the assumption that automated work hours are reintegrated in work at productivity level of today.
[2]Previous assessment of work automation before the rise of generative AI.
[3]Based on 47 countries, representing about 80% of world employment.
Source: Conference Board Total Economy database; Oxford Economics; McKinsey Global Institute analysis

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The capabilities of generative AI vastly expand the pool of work activities with the potential for technical automation. That in turn has sped up the pace at which automation may be deployed and expanded the types of workers who will experience its impact. Like other technologies, its ability to take on routine tasks and work can increase human productivity, which has grown at a below-average rate for almost 20 years.[18] It can also offset the impact of aging, which is beginning to put a dent in workforce growth for many of the world's major economies. But to achieve these benefits, a significant number of workers will need to substantially change the work they do, either in their existing occupations or in new ones. They will also need support in making transitions to new activities.

Considerations for businesses and society

History has shown that new technologies have the potential to reshape societies. Artificial intelligence has already changed the way we live and work—for example, it can help our phones (mostly) understand what we say, or draft emails. Mostly, however, AI has remained behind the scenes, optimizing business processes or making recommendations about the next product to buy. The rapid development of generative AI is likely to significantly augment the impact of AI overall, generating trillions of dollars of additional value each year and transforming the nature of work.

But the technology could also deliver new and significant challenges. Stakeholders must act—and quickly, given the pace at which generative AI could be adopted—to prepare to address both the opportunities and the risks. Risks have already surfaced, including concerns about the content that generative AI systems produce: Will they infringe upon intellectual property due to “plagiarism” in the training data used to create foundation models? Will the answers that LLMs produce when questioned be accurate, and can they be explained? Will the content generative AI creates be fair or biased in ways that users do not want by, say, producing content that reflects harmful stereotypes?

There are economic challenges too: the scale and the scope of the workforce transitions described in this report are considerable. In the midpoint adoption scenario, about a quarter to a third of work activities could change in the coming decade. The task before us is to manage the potential positives and negatives of the technology simultaneously (for more about the potential risks of generative AI, see Box 5). Here are some of the critical questions we will need to address while balancing our enthusiasm for the potential benefits of the technology with the new challenges it can introduce.

Box 5

Using generative AI responsibly

Generative AI poses a variety of risks. Stakeholders will want to address these risks from the start.

Fairness: Models may generate algorithmic bias due to imperfect training data or decisions made by the engineers developing the models.

Intellectual property (IP): Training data and model outputs can generate significant IP risks, including infringing on copyrighted, trademarked, patented, or otherwise legally protected materials. Even when using a provider's generative AI tool, organizations will need to understand what data went into training and how it's used in tool outputs.

Privacy: Privacy concerns could arise if users input information that later ends up in model outputs in a form that makes individuals identifiable. Generative AI could also be used to create and disseminate malicious content such as disinformation, deepfakes, and hate speech.

Security: Generative AI may be used by bad actors to accelerate the sophistication and speed of cyberattacks. It also can be manipulated to provide malicious outputs. For example, through a technique called prompt injection, a third party gives a model new instructions that trick the model into delivering an output unintended by the model producer and end user.

Explainability: Generative AI relies on neural networks with billions of parameters, challenging our ability to explain how any given answer is produced.

Reliability: Models can produce different answers to the same prompts, impeding the user's ability to assess the accuracy and reliability of outputs.

Organizational impact: Generative AI may significantly affect the workforce, and the impact on specific groups and local communities could be disproportionately negative.

Social and environmental impact: The development and training of foundation models may lead to detrimental social and environmental consequences, including an increase in carbon emissions (for example, training one large language model can emit about 315 tons of carbon dioxide).[1]

1 Ananya Ganesh, Andrew McCallum, and Emma Strubell, "Energy and policy considerations for deep learning in NLP," *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, June 5, 2019.

Companies and business leaders

How can companies move quickly to capture the potential value at stake highlighted in this report, while managing the risks that generative AI presents?

How will the mix of occupations and skills needed across a company's workforce be transformed by generative AI and other artificial intelligence over the coming years? How will a company enable these transitions in its hiring plans, retraining programs, and other aspects of human resources?

Do companies have a role to play in ensuring the technology is not deployed in "negative use cases" that could harm society?

How can businesses transparently share their experiences with scaling the use of generative AI within and across industries—and also with governments and society?

Policy makers
What will the future of work look like at the level of an economy in terms of occupations and skills? What does this mean for workforce planning?

How can workers be supported as their activities shift over time? What retraining programs can be put in place? What incentives are needed to support private companies as they invest in human capital? Are there earn-while-you-learn programs such as apprenticeships that could enable people to retrain while continuing to support themselves and their families?

What steps can policy makers take to prevent generative AI from being used in ways that harm society or vulnerable populations?

Can new policies be developed and existing policies amended to ensure human-centric AI development and deployment that includes human oversight and diverse perspectives and accounts for societal values?

Individuals as workers, consumers, and citizens
How concerned should individuals be about the advent of generative AI? While companies can assess how the technology will affect their bottom lines, where can citizens turn for accurate, unbiased information about how it will affect their lives and livelihoods?

How can individuals as workers and consumers balance the conveniences generative AI delivers with its impact in their workplaces?

Can citizens have a voice in the decisions that will shape the deployment and integration of generative AI into the fabric of their lives?

Technological innovation can inspire equal parts awe and concern. When that innovation seems to materialize fully formed and becomes widespread seemingly overnight, both responses can be amplified. The arrival of generative AI in the fall of 2022 was the most recent example of this phenomenon, due to its unexpectedly rapid adoption as well as the ensuing scramble among companies and consumers to deploy, integrate, and play with it.

All of us are at the beginning of a journey to understand this technology's power, reach, and capabilities. If the past eight months are any guide, the next several years will take us on a roller-coaster ride featuring fast-paced innovation and technological breakthroughs that force us to recalibrate our understanding of AI's impact on our work and our lives. It is important to properly understand this phenomenon and anticipate its impact. Given the speed of generative AI's deployment so far, the need to accelerate digital transformation and reskill labor forces is great.

These tools have the potential to create enormous value for the global economy at a time when it is pondering the huge costs of adapting and mitigating climate change. At the same time, they also have the potential to be more destabilizing than previous generations of artificial intelligence. They are capable of that most human of abilities, language, which is a fundamental requirement of most work activities linked to expertise and knowledge as well as a skill that can be used to hurt feelings, create misunderstandings, obscure truth, and incite violence and even wars.

We hope this research has contributed to a better understanding of generative AI's capacity to add value to company operations and fuel economic growth and prosperity as well as its potential to dramatically transform how we work and our purpose in society. Companies, policy makers, consumers, and citizens can work together to ensure that generative AI delivers on its promise to create significant value while limiting its potential to upset lives and livelihoods. The time to act is now.[19]

Endnotes

1 "A future that works: Automation, employment, and productivity," McKinsey Global Institute, January 12, 2017.

2 Ryan Morrison, "Compute power is becoming a bottleneck for developing AI. Here's how you clear it.," *Tech Monitor*, updated March 17, 2023.

3 "Introducing ChatGPT," OpenAI, November 30, 2022; "GPT-4 is OpenAI's most advanced system, producing safer and more useful responses," OpenAI, accessed June 1, 2023.

4 "Introducing Claude," Anthropic PBC, March 14, 2023; "Introducing 100K Context Windows," Anthropic PBC, May 11, 2023.

5 Emma Roth, "The nine biggest announcements from Google I/O 2023," *The Verge*, May 10, 2023.

6 Pitchbook.

7 Ibid.

8 Erik Brynjolfsson, Danielle Li, and Lindsey R. Raymond, *Generative AI at work*, National Bureau of Economic Research working paper number 31161, April 2023.

9 Peter Cihon et al., *The impact of AI on developer productivity: Evidence from GitHub Copilot*, Cornell University arXiv software engineering working paper, arXiv:2302.06590, February 13, 2023.

10 Michael Nuñez, "Google and Replit join forces to challenge Microsoft in coding tools," VentureBeat, March 28, 2023.

11 Joe Coscarelli, "An A.I. hit of fake 'Drake' and 'The Weeknd' rattles the music world," New York Times, updated April 24, 2023.

12 "Job openings and labor turnover survey," US Bureau of Labor Statistics, accessed June 6, 2023.

13 The comparison is not exact because the composition of work activities between 2016 and 2023 has changed; for example, some automation has occurred during that time period.

14 A more skills-based approach to workforce development predates the emergence of generative AI.

15 *Global economic prospects*, World Bank, January 2023.

16 Yaron Shamir, "Three factors contributing to fewer people in the workforce," *Forbes*, April 7, 2022.

17 "The U.S. productivity slowdown: an economy-wide and industry-level analysis," Monthly Labor Review, US Bureau of Labor Statistics, April 2021; Kweilin Ellingrud, "Turning around the productivity slowdown," McKinsey Global Institute, September 13, 2022.

18 "Rekindling US productivity for a new era," McKinsey Global Institute, February 16, 2023.

19 The research, analysis, and writing in this report was entirely done by humans.

Appendix

I. Scope of the investment landscape

For data on investment flows into generative AI, we relied on Pitchbook.

For data on investments in artificial intelligence overall, we referred to *The AI Index 2023 annual report* by Stanford University's Institute for Human-Centered AI.[1]

II. How we sized the use case value potential

Overall objective
The objective was to estimate the potential economic impact of generative AI and foundation models using a bottom-up assessment of the most relevant use cases across business functions and industries. The resulting analysis approximates the potential value of generative AI and foundation models in terms of productivity, or the equivalent amount by which the technologies could reduce the global functional spending required to maintain current revenue levels.

Summary of our approach
Our micro-to-macro use-case-based approach to estimating the potential impact of generative AI included the following:

How we estimated the impact of generative AI across industries. We identified and cataloged generative AI and foundation model use cases with input from experts from McKinsey's industry and functional practices. While the resulting generative AI and foundation model use case database is not necessarily exhaustive, it was meant to be as comprehensive as possible.

Business function overview

Business function	Definition
Customer operations	Activities related to customer care, such as call centers
Software development	Activities related to designing, coding, testing, and maintaining software programs, applications, and systems, such as enterprise resource planning tools and other internal tools, that meet specific business or customer needs
Product R&D	Activities related to new products or services, such as market and academic research, ideation, and simulations used in the early stages of product development, and heavy simulations, prototyping, and testing used later in the development process
Legal, risk, and compliance	Activities related to risk and compliance, such as labor relations, litigation support, and contract creation

[1] *The AI Index 2023 annual report*, Institute for Human-Centered AI, Stanford University, April 2023.

Marketing and sales	Activities related to B2B and B2C marketing, for example, market research, creative, marketing strategy, and sales, customer preparation, and interaction support, including pricing analytical support, price scraping, and item matching
IT	Activities related to internal information tech systems, such as administrative and IT help desk, but excluding software engineering for internal solutions (captured within software engineering)
Talent and organization (including HR)	Activities related to organizational performance and talent management; for example, organizational health assessment, recruiting, learning and development, and human resources
Finance and strategy	Activities related to financial operations, such as general accounting, financial planning and analysis, and accounts payable and receivable, as well as internal strategy functions such as market intelligence and strategic planning

Estimate generative AI's impact in individual use cases. We collected expert inputs, the results of McKinsey internal experiments, and published research to estimate the potential quantitative range of impact (in both cost savings and revenue uplift) and to gain qualitative findings from functions within individual use cases.[2] Where generative AI and foundation models are assumed to increase revenue, we recast the effect as an increase in productivity that would be the equivalent of the reduced level of spending required to maintain the same level of output (thus enabling comparability with cost reductions).

Our analysis of use cases only examines the direct impact of generative AI on productivity. They do not incorporate secondary benefits, such as the economic impact of hiring a more capable employee or hiring employees more rapidly.

Estimate the impact across industries
To estimate the impact of generative AI and foundation models across industries, we scaled our analysis from a functional lens to an industry lens for each industry, assessing the weight of functional costs. For instance, customer operations costs are higher in the telecom industry than in aerospace.

For each use case, the relevant costs were defined to account only for activities for which generative AI or foundation models were likely to deliver productivity gains. For example, the cost base against which we assessed productivity gains for the marketing function excludes ad buying costs because the use cases we assessed for generative AI in that function would have no productivity impact on the "ad buying" activity.

A. Global revenues for each industry in 2022 were sourced from IHS Markit and Oxford Economics.

B. We estimated the functional cost for a function as a percentage of total revenue in an industry based on published data, industry experts, and McKinsey benchmarks.

2 *Generative AI at work*, April 2023.

C. For each function, we estimated the relevant costs (considering only underlying activities affected by our use cases) as a portion of overall spending on a function, again informed by published data, industry experts, and McKinsey benchmarks.

D. For each use case, we quantified the potential impact of generative AI and foundation models based on the impact (either cost or revenue) as a function of the relevant addressable spending.

E. We then calculated the impact by industry by aggregating the technology's impact on use cases in an industry across functions.

Limitations of our impact analysis

For each use case, our analysis of the impact of generative AI and foundation models draws a conservative base case and a more accelerated upside potential. The estimates are based on existing data and experiences, and these estimates could be updated over time. Additionally, the list of use cases is not exhaustive but is as comprehensive as possible, given our methods.

The estimates in this report should be treated as directional rather than precise, given the nature of the technology and the wide range of uncertainty involved in the future development of generative AI. We welcome challenges to our analysis as well as additional inputs that would refine and enhance it.

Comparison with the 2018 report *Notes from the AI frontier: Applications and value of deep learning*

To estimate the incremental impact that generative AI and foundation models could have in comparison to the value of artificial intelligence overall, we updated our 2018 estimates of the value that could be created through deployment of advanced analytics and previous generations of artificial intelligence.[3]

This research incorporates 2022 updates to baseline financial variables such as industry revenues, enabling updates to the total potential economic impact of advanced analytics and AI exclusive of generative AI and foundation models.

III. How we estimated the impact of generative AI on the potential for technical automation

This report continues and adapts the methodology and findings of the January 2017 McKinsey Global Institute report, *A future that works: Automation, employment, and productivity*.[4] We recommend that readers refer to the technical appendix of that report for our full methodology. Here, we outline updates we have incorporated in the automation adoption estimation process and a brief overview of the steps involved in assessing automation adoption, together with methodology to estimate the impact of automation on work hours (represented as full-time equivalents, or FTEs, where one FTE equals 2,080 hours) and GDP impact. (For additional research on the impact of automation on work transformation, please see Box A1, "Overview of select recent studies on the impact of generative AI on work automation").

[3] "Notes from the AI frontier," April 17, 2018.
[4] "Harnessing automation for a future that works," January 12, 2017.

Box A1

Overview of select recent studies on the impact of generative AI on work automation

Goldman Sachs

Citation	Joseph Briggs et al., *The potentially large effects of artificial intelligence on economic growth,* Goldman Sachs, March 26 2023
Unit of analysis	Occupations; industries
Scope	United States and Europe (with extrapolation globally)

Approach summary
- Estimate the share of total work exposed to labor-saving automation by AI by occupation and industry.
- Thirteen work activities are classified as exposed to AI automation based on a review on the probable use cases of Generative AI, and a share of each occupation's total workload that AI has the potential to replace is estimated by applying the O*Net "level" scale and taking an importance- and complexity-weighted average of essential work tasks.

Data collection
- O*NET and European ESCO databases were used to obtain information about task contents and occupations.

Key relevant findings
- In the United States and Europe, two-thirds of jobs are being exposed to some degree of AI automation; 25 percent of current work tasks could be automated. Extrapolating globally, 18 percent of work could be automated by AI, with scenarios ranging from 15 to 35 percent, depending on different levels of AI capabilities.
- Seven percent of US employment would be substituted by AI, and 300 million jobs globally would be exposed to automation, assuming jobs for which at least 50 percent of importance- and complexity-weighted tasks are exposed to automation are likely to be substituted by AI, 10 to 49 percent are likely to be complemented, and less than 10 percent are unlikely to be affected.
- Generative AI could raise annual US labor productivity growth by 1.5 percentage points over a ten-year period, assuming that 7 percent of workers are fully displaced but able to find employment at slightly less productive positions, that partially exposed workers increase their productivity, and that roughly half of firms adopt generative AI during that period. Scenarios of productivity growth range from 0.3 to 3.0 percentage points depending on the difficulty level of tasks generative AI could perform, how many jobs are automated, and the speed of adoption.
- Extrapolating globally, annual productivity growth from generative AI could be 1.4 percentage points over ten years.

Open AI, OpenResearch, University of Pennsylvania

Citation	Tyna Eloundou et al., *GPTs are GPTs: An early look at the labor market impact potential or large language models,* Cornell University arXiv economics working paper, arXiv:2303.10130, March 2023
Unit of analysis	Skills; occupation groups; industries
Scope	United States

Approach summary
- Investigate implications of large language models (LLMs) on the United States labor market using three exposure categories (exposure being a measure of whether access to an LLM would reduce the time required to complete a specific detailed work activity or task by at least 50 percent): 1 is no exposure, 2 is direct exposure, and 3 is LLM+ exposure (that is, additional software could be developed on top of the LLM) to reach 50 percent.
- Exposure was assessed by human annotators and GPT-4.

Data collection
- The working paper used the O*NET database (1,016 occupations, 2,087 detailed work activities [DWA], and 19,265 tasks). DWAs were first aggregated to task level then occupation level.
- Employment and wage data were obtained from the 2020 and 2021 occupational employment series provided by the US Bureau of Labor Statistics.

Key relevant findings
- About 80 percent of the US workforce could have at least 10 percent of their work tasks exposed to LLMs (the time required to complete these tasks reduced by at least 50 percent).
- Nineteen percent of workers may see at least 50 percent of their tasks exposed to LLMs.
- About 15 percent of all worker tasks in the United States could be performed significantly faster at the same level of quality with LLMs, but this share increases to 47 to 56 percent when incorporating software and tooling built on top of LLMs.
- Effects of LLMs are relevant to all wage levels, but high-income occupations and occupations requiring at least a bachelor's degree may be more exposed than others.

Box A1 (continued)

Princeton University, University of Pennsylvania, New York University

Citation	Edward W. Felten, Manav Raj, and Robert Seamans, *Occupational heterogeneity in exposure to generative AI,* SSRN, April 2023
Unit of analysis	Occupations
Scope	United States

Approach summary

- Estimate exposure scores of the occupations most exposed to advances in AI language modeling and AI image generation in US workforce.
- Ten AI applications (such as image generation, language modeling, and real-time video games) are linked to 52 human abilities (such as oral expression) through crowdsourced assessments of relatedness, which are mapped to approximately 800 occupations to create exposure scores for language modeling and image generation.

Data collection

- O*NET database provides mapping from occupations to human abilities, including prevalence and importance scores.
- American Community Survey five-year estimates from 2021 provided by IPUMS were used to provide data on demographics.

Key relevant findings

- The average occupational exposure to language modeling is higher than to image generation.
- Occupations most exposed to language modeling require communication and language-based abilities, while those most exposed to image generation require visual or spatial abilities.
- Highly-educated, highly-paid, white-collar occupations may be most exposed to generative AI.
- Strong, positive correlation between generative AI exposure and median salaries, required education levels, and the presence of creative abilities within an occupation.
- There is positive correlation between generative AI exposure and percent of female, White, and Asian representation in occupations in US workforce. There is negative correlation between generative AI exposure and percent of male, Black, and Hispanic representation.

McKinsey & Company

Citation	*The economic potential of generative AI: The next productivity frontier,* McKinsey Global Institute, June 2023
Unit of analysis	Function; industries; occupations
Scope	Forty-seven countries covering 80 percent of global workforce

Approach summary

- Estimate when technologies including generative AI will reach median and top quartile human performance against 18 different capabilities through expert assessments.
- Map these assessments to DWAs and occupations to develop scenarios of technical automation potential increasing over time
- Model scenarios for automation adoption for DWAs, occupations and countries that include technical automation potential, solution integration timelines, economic feasibility versus wage rates, and technology diffusion rates.

Data collection

- Occupation and detailed work activity data was sourced from O*NET.
- Employment and wage data was sourced from national statistical agencies (such as the US Bureau of Labor Statistics).

Key relevant findings

- The capabilities of generative AI have increased the share of time spent on work activities that theoretically could be automated by adapting technologies available in 2023 from about half to two-thirds of all working time.
- The pace of adoption is likely to accelerate, with estimates that half of today's work activities could be automated in scenarios that range from 2030 to 2060, with a midpoint in 2045—or roughly a decade earlier than the midpoint estimate produced by our 2017 scenarios.
- Experts' assessment shows much of this acceleration in the potential for technical automation is due to generative AI's increased natural language capabilities.
- Unlike most automation in the past, the impact of generative AI will fall most heavily on occupations requiring higher levels of education and commanding higher wages.
- Generative AI could increase labor productivity by 0.1 percent to 0.6 percent annually over the next ten to 20 years. When combined with other technologies, automation overall could contribute 0.2 to 3.3 percent annually to productivity growth, assuming labor is redeployed at today's productivity levels and not including general equilibrium effects.

Source: US Bureau of Labor Statistics O*NET; McKinsey analysis

McKinsey & Company

We assessed the technical potential for automation across the global economy through an analysis of the component activities of each occupation. Our analysis covers 47 countries representing more than 80 percent of the global economy. We used the US Bureau of Labor Statistics O*Net data set that maps about 850 occupations to approximately 2,100 detailed work activities.

Each detailed work activity was assessed against 18 capabilities that could potentially be automated based on the level of performance necessary to successfully perform that activity. These assessments were informed by academic research, McKinsey expertise, and industry experts. We defined four possible levels of requirement for each capability, ranging from not required to top-quartile human performance. Please refer to exhibits A1 to A4 of the technical appendix in the January 2017 McKinsey Global Institute report, *A future that works: Automation, employment, and productivity* for more details on the capabilities and the four requirement levels.[5]

Assigning the required level of capabilities to activities
We used a machine learning algorithm to score the approximately 2,100 work activities in relation to the 18 performance capabilities. To train the algorithm, we devised a list of keywords with input from experts. The algorithm scores each activity by matching keywords from the capability to the activity title. These assessments were checked manually, and where we found anomalies, special requirements, or a need for nuance, we made adjustments—for example, in assessing the level of capabilities needed to navigate in extreme weather or on uneven surfaces and other unpredictable settings, or the different physical capabilities required by a kindergarten teacher compared with a middle school teacher.

1. Modeling of automation adoption timelines
Our adoption model assesses the automation development and adoption timeline at activity level for more than 850 occupations across 19 sectors and 47 countries that represent more than 80 percent of the global economy. We divide the adoption process into four phases: technical feasibility, solution development, economic feasibility, and end-user adoption.

Technical feasibility
For a detailed work activity to be automated, technology must exist that performs at the required level for each of the 18 capabilities. To update the progression scenarios for the performance capabilities over time, we surveyed experts in generative AI. We also conducted interviews with industry leaders and academic experts. Based on these assessments, we updated the expected time frames to reach each level of performance for each capability. In our analysis and interaction with experts, we focused on the following capabilities that could be affected by generative AI:

— Natural-language understanding

— Natural-language generation

— Social and emotional reasoning

— Emotional and social output

— Social and emotional sensing

— Coordination with multiple agents

— Generating novel patterns or categories

— Creativity

[5] *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*, McKinsey Global Institute, November 28, 2017.

— Logical reasoning and problem solving

— Output articulation or display

— Sensory perception

Solution development
We also updated our estimates for how long it would take to develop a solution that could integrate automation technologies once technical feasibility was established, based on a series of expert interviews. The original estimates were developed by examining the development time and technical capabilities for more than 100 previously developed automation solutions, including hardware and software solutions.

Economic feasibility
Once a solution is developed, we assume activities will start to be automated when the cost of the solution falls below the level of wages paid to a human to do that activity. For this calculation, we accounted for the evolution of solution costs as well as the evolution of wages.

Solution cost evolution
Based on the capability requirements, solutions are classified into two categories: hardware and software. If a solution requires sensory perception, fine motor skills and dexterity, gross motor skills, or mobility, it is classified as a hardware solution. Otherwise, it is classified as a software solution. For a given solution, the initial cost is estimated as a percentage of the highest hourly wage for the corresponding activity across all the countries we modeled. We estimated the initial cost by examining several examples of solutions developed using different mixes of hardware and software. Based on our research, most software solutions have relatively low initial costs as a percentage of the human labor cost. Some solutions that require a combination of both software and hardware components have a higher initial cost. To be conservative, we excluded certain solutions with advantages that could be derived only from very specific scenarios or that include noneconomic benefits such as increased quality and efficiency or decreased error rates. The range of initial solution costs we modeled is 20 to 70 percent of the highest hourly wage for the corresponding activity for hardware, and 0 to 20 percent for software.

In our model, solution costs decrease as technology advances. Hardware solution costs decline by 16.0 percent per year, and software solution costs decline by 5.3 percent per year. We triangulate the consumer price index and supplier surveys to estimate the reduction in hardware solution costs. For this, we use computer software and accessories indexes to estimate software solution cost reduction. For consumer price inflation, we used consumer price index data for personal computers and peripheral equipment. For computer software and accessories, we use data from the US Bureau of Labor Statistics. For software solution costs, we use a survey of prices from the International Federation of Robotics. Further work could be done to refine the estimation; however, given software's low starting cost, annual reductions have little impact on final automation results.

Wage evolution
We model the wage evolution for each country in two stages. From 2023 to 2030, we apply country-level growth estimates for all countries and convert them into 2010 constant US dollars by dividing nominal GDP by the corresponding country-level price deflator (2010 base) and multiply the exchange rate to the dollar (2010 base). We then calculate a CAGR for each country from 2022 to 2030. For 2030 onward, we grouped the 47 countries for which we have data into two cohorts using a cutoff country-level annual wage, based on the wage distribution from 2022 to 2030. Countries within the same cohort grow at the same rate. We reclassify countries each year. As a country advances into the next cohort, the appropriate growth rate is applied.

Adoption and deployment
Adoption can start once automation solutions are economically feasible, but several factors can hinder or enable the timing and the pace of adoption. Solutions requiring different technologies have varying levels of ease of integration. It takes time to integrate capabilities into current technical platforms and combine them into an organic entity. Barriers also exist on the organization side. Human talent and organization structures might act as bottlenecks to implementation. Policies and regulations could also slow down or accelerate technology innovation and adoption. Finally, depending on their preferences, consumers might have varied levels of acceptance for automated solutions that could affect the pace of adoption.

To incorporate all these factors, we used the mathematics of the Bass diffusion model, a well-known and widely used function in forecasting, especially for new product sales forecasting and technology forecasting.

$$\frac{f(t)}{1-F(t)} = (p + qF(t))$$

F(t) is the installed base fraction (that is, adoption of given technology or product) and f(t) is the corresponding rate of change.

The function in our case also contains two key parameters: p parameter (the inherent tendency of consumers to adopt new technology), and q parameter (the tendency of consumers to adopt based on peer adoption). Parameters are estimated through ordinary least square regression. In the absence of data, p and q parameter values from meta analyses can be used if a saturation value is known or can be guessed.

We then simulated two scenarios for historic technology adoption curves. The technologies we used are stents, airbags, laparoscopic surgery, MRI, smartphones, TVs, antilock braking systems, online air booking, cellphones, color TVs, SX/EW leaching, personal computers, electronic stability control, instrument landing systems, dishwashers, and pacemakers. The fitted values of parameters p and q are consistent with other academic research. It takes about five years to reach 50 percent adoption in the earliest scenario and approximately 16 years in the latest scenario.

2. Work hours that could be automated
The impact of automation on work hours across different capability levels is estimated below for the technical automation potential and automation adoption:

Impact by occupation by scenario: Number of FTEs X % automation estimate by scenario

Impact by activity: Number of FTEs X time spent on activity per year[6] X percent automation estimate by scenario

Impact by occupation group[7] : $\Sigma_{occupation}$ (Number of FTEs X percent automation estimate by scenario)

3. Impact of automation on productivity
We used GDP per FTE as the measure of productivity. We calculated automation output under different scenarios by multiplying the projected number of FTEs by the estimated automation adoption rate. To maintain consistency with other data sources, we made several additional assumptions. We considered only job activities that are available and well defined as of the date of this report. Also, to be conservative, we assumed that automation has a labor

[6] FTEs whose job titles include these detailed work activities.
[7] For occupations included within the occupation group.

substitution effect but no other performance gains. Finally, we assumed that labor replaced by automation will rejoin the workforce at the same level of productivity as today. We also assumed that additional output from automation will not decrease, even if the total number of FTEs declines as a result of demographic changes.

Under the assumptions outlined above, we calculated the GDP impact of automation adoption by country as follows:

Additional GDP impact of automation = FTE impact of automation X productivity

The additional GDP impact of automation is then added to 2022 GDP to estimate the productivity impact of automation.

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