



EKONOMİK ARAřTIRMALAR

SEPTEMBER 2026

UNDERSTANDING TECHNOLOGICAL TRANSFORMATION

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What Have You Done for Humanity Today?

While humanity is advancing on many fronts, have you noticed how the quality of our conversations seems to be moving the other way? It seems that whenever we have a meaningful discussion and a disagreement arises or we cannot answer a question, someone inevitably asks, “Shall we ask AI?”. I do not always say it aloud, but my instinctive response is often: “Let’s not. Not yet.” Let us first talk, reason and test the limits of what we know. If that is not enough, then let us research.

This is not a criticism of artificial intelligence. The issue, as ever, is not the technology itself, but how we choose to use it. Are we seeking effortless answers to every question, necessary or otherwise? Or are we using technology to drive structural improvement?

We also tend to read change backwards, through the lens of the latest trend. These days, we are talking about artificial intelligence. Before, the digital transformation was in fashion. And yet, if we pause, step back and widen the lens, a broader need becomes clear: the real conversation should be about the technological transformation.

To view our fundamental challenge merely as one of converting analogue and manual processes into digital ones would be too narrow a perspective. Instead, we need to transform how we work, what we produce and how we compete, while safeguarding the public interest, respecting the planet, considering future generations, improving conditions for disadvantaged groups and leaving no one behind.

Once this becomes the objective, as it should, we no longer begin by asking, “Can we digitalize this process?” Rather, we ask, “How can we do this differently and better?” The answer opens a wider field, one that includes AI and digitalization but extends well beyond both.

From this perspective, humans are not casualties of a transformation in which robots will brutally take over human jobs, but stakeholders whose lives should improve through it. The green transformation, public objectives and responsibility become integral to innovation.

In this report, we approach technological transformation through a development lens - not as something that is merely happening to us, but as a process which we can plan for and shape. By bringing it together with the new industrial policy framework, we aim to move the debate beyond fashionable concepts and towards tangible action - and ultimately, to ask technology itself: What have you done for humanity today? Enjoy the read.

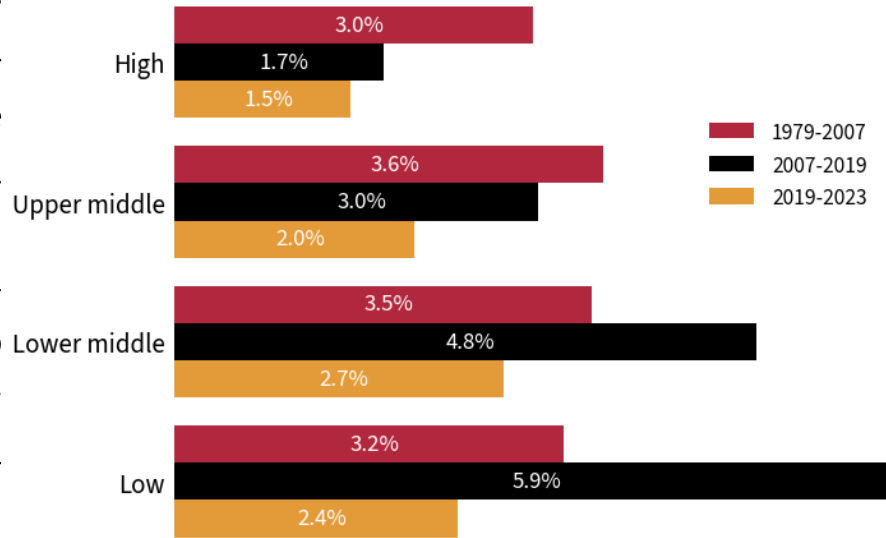
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Why Do We Study Technology?

During the long period following the Second World War and lasting until the late 1970s, which is often referred to as the golden age of capitalism, many economies—particularly today’s advanced economies—enjoyed a period of unprecedented growth. In the subsequent long period, extending from the early 1980s and continuing until the global financial crisis, economic growth was slower. However, the slowdown in growth became even more pronounced following the outbreak of the global financial crisis in 2008. The median growth rate in high-income countries declined from 3.0% in the 1979–2007 period to 1.7% in 2007–2019. In the 2019–2023 period, which largely reflected the effects of the pandemic,

Figure 1. Median Annual Compound Growth Rate by Income Group



Source: Penn World Table 11.0, TSKB Economic Research

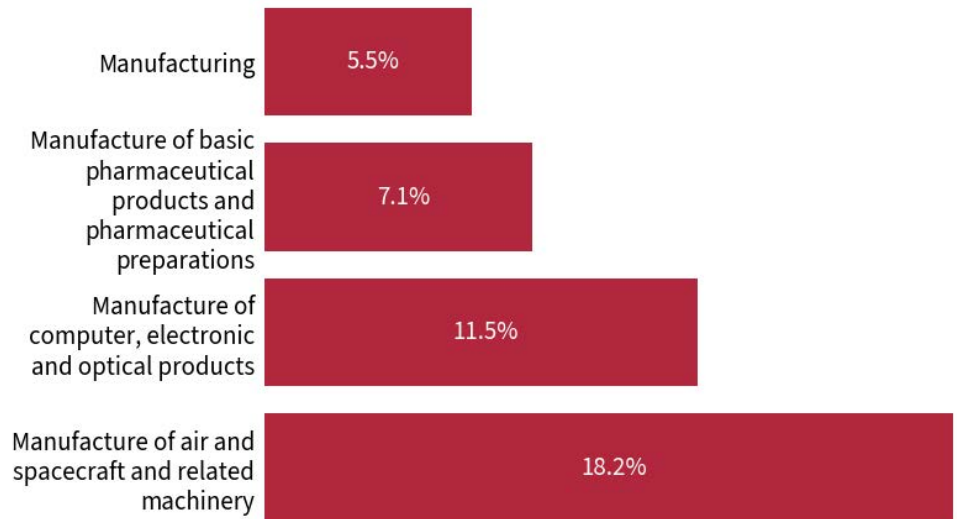
economic growth declined further to 1.5%. While lower-middle-income and low-income countries recorded a higher median rate of growth in the 2007–2019 period when compared to the previous period, they also suffered significantly slower growth following the pandemic (Figure 1).

The slowdown in economic growth is also evident in potential growth. Potential growth refers to the growth rate of an economy’s potential output, or in other words, the level of output which an economy can produce under conditions of full capacity utilization and full employment. Nearly all advanced economies and around 60% of emerging market and developing economies recorded lower potential growth in the 2011–2021 period than their average over the 2000–2010 period (by 0.8 and 1.0 percentage points, respectively) (Celik et al., 2023). Moreover, each of the key drivers of growth—total factor productivity, labor supply and the capital stock—is growing more slowly.

Turning to Türkiye, although there have been positive developments in some technology groups in the manufacturing industry, progress remains limited. Between 2010 and 2025, real manufacturing output grew by an average of 5.5% per year, while low- and medium-low-technology pro-

duction grew by 4.2% and 5.3%, respectively. By contrast, medium-high- and high-technology production increased by 6.8% and 11.5%, respectively. Production in all three activities classified as high-tech industries grew faster than total manufacturing output. The manufacture of air and spacecraft and related machinery, considered part of the defense industry, stood out significantly in this group, with production surging by 18.2% over the period (Figure 2)¹.

Figure 2. Annual Compound Growth in High-Tech Production 2010-2025

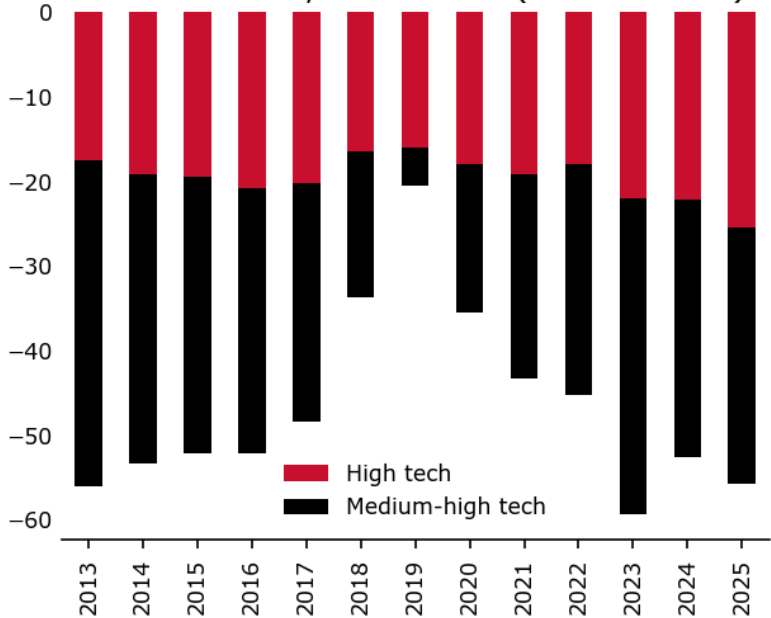


Note: For the manufacture of air and spacecraft and related machinery, 2009-2024 data are used. For more information, see the footnote in the text.

Source: TurkStat, TSKB Economic Research

Despite this bright picture, the share of high-tech products in total manufacturing sales edged up only modestly, from 3.3% in 2016 to 3.6% in 2025. The share of medium-high-tech products in total manufacturing sales increased from 25.0% to 28.8%. Thus, despite a substantial increase in production, the share of high-tech products in total manufacturing output remains limited due to its low base. At the same time, persistent foreign trade deficits have become a characteristic in high- and medium-high tech products (Figure 3).

Figure 3. Trade Balance for High and Medium-High Tech Products, 2013-2025 (Billion dollars)



Source: TurkStat, TSKB Economic Research

¹Seasonally and calendar-adjusted industrial production indices are used for manufacturing, pharmaceuticals and the manufacture of computers, electronic and optical products. Since TurkStat does not provide a production index for the manufacture of air and spacecraft and related machinery, the production value for this activity in the Annual Industry and Service Statistics database was deflated using the producer price index for other transport equipment not elsewhere classified to remove the effect of price changes.

The slowdown in global economic growth, the accompanying slowdown in potential growth and Türkiye's persistent technology gap call for a reconsideration of technology and industrial policy. To this end, we first establish the background by discussing some key trends which are of importance in the context of technological transformation. Since rethinking technology policy requires, above all, an understanding of technology itself, the following section focuses on technology and develops a framework for technological transformation. We then turn to artificial intelligence, which has entered our lives as a radical technology. Finally, we discuss what technology and industrial policy can do to manage technological transformation.

Background

The Information and Communication Technology Revolution

Although growth in the global economy has generally tended to slow, some economic activities have expanded much more rapidly than the economy as a whole. For example, the production of technologies such as semiconductors (chips), computers and peripheral equipment, software and telecommunications equipment and services—the main drivers of the information and communication technology (ICT) revolution that began in the 1970s—have surged at a strikingly faster pace than the economy as a whole (Baily & Bosworth, 2014). As a result, the macroeconomic impact of productivity gains arising both from advances in the production of these technologies and from their adoption across other production activities started to be felt in the mid-1990s (Gordon, 2016). These technologies also allow production to be moved beyond national borders and for it to be organized on a global scale.

The production of semiconductors (chips), which are among the high-tech ICT products, requires substantially higher R&D and fixed capital expenditure than many other manufacturing activities (East & Kaspar, 2023; SIA, 2025). The rise in investment expenditure on artificial intelligence (AI) also clearly reflects this capital intensity. In particular, AI applications based on deep learning and artificial neural networks require unprecedented levels of computing power. This enormous demand for computing requires capital investment that relies heavily on chips (processors and memory chips) and the data centers that house them. As a result, rising investment in AI infrastructure is reaching a scale capable of affecting the economy as a whole.

Concentration

Concentration may be one of the words that best describes the AI ecosystem. US-based firms lead in the development of AI models by a wide margin with China being the only country to even come close to the United States in this respect. For example, during 2025, 59 notable models were developed in the United States, 35 in China and only two in Europe (HAI, 2026). Chips designed by US-based Nvidia account for by far the largest share of global computing capacity. The Taiwan-based chip manufacturer, TSMC, meanwhile, produces almost all advanced AI chips. As of 2025, the United States was home to 5,247 data centers, more than ten times as many as in any other country. Five US-based companies—Amazon, Google, Meta, Microsoft, and Oracle—provide a large share of the computing capacity required for AI applications. The capital expenditure of these five companies has surged since 2024, reaching USD 412 billion in 2025, equivalent to 1.31% of US GDP (Allen, 2026). This reflects the unprecedented pace of the investment boom in the United States (Rungcharoenkitkul, 2026).

Technological transformation is also affecting foreign direct investment (FDI) flows. Between 2010–2025, when global gross domestic product (GDP) and trade recorded a relatively steady expansion, FDI growth was both more volatile and slower. However, FDI did expand in 2024 and 2025. Moreover, greenfield investment in sectors considered strategic from the perspective of industrial policy and economic security—such as AI infrastructure and AI-related technologies, advanced and sensitive technologies, critical minerals, clean energy, and semiconductors—expanded at a more rapid pace than the average. In contrast, greenfield investment projects in manufacturing activities which are highly integrated into global supply chains, such as in the electronics and electrical equipment, automotive, machinery and equipment, and textiles, apparel and leather sectors experienced a significant decline in both number and value (UNCTAD, 2026). This is making it more difficult for many developing countries to benefit from global supply chains.



Greenfield investment in strategic sectors grew by 39% annually between 2020 and 2025 to reach USD 576 billion. Consequently, the share of strategic sectors in total greenfield investment increased from 16% in 2020 to 44% in 2025. Semiconductors and AI infrastructure and AI-related technologies stood out from other sectors, with average annual growth rates of 54% and 47%, respectively. Greenfield investment in clean energy and critical minerals grew by 17%, while investment in advanced and sensitive technologies grew by 8%. Clean energy technologies, which had increased their share among strategic sectors until 2023, lost some ground in 2024–2025 as AI investment surged, reflecting a concentration of technology within greenfield investment in strategic sectors. Another form of concentration is evident in the geographical distribution of investment. The three largest investing countries or country groups accounted for 72% of total greenfield investment, while the three largest recipients accounted for 56% of total investment. In addition, 72% of greenfield investment in strategic sectors was directed towards high-income countries and 18% to upper-middle-income countries. This concentration is shaped by firm-level factors such as economies of scale, supply-chain integration, and technological capabilities, as well as factors reflecting the effects of policies such as incentive regimes, local-content incentives and regulatory compliance (UNCTAD, 2026).

The Rise of Industrial Policy

Another key dynamic in the background has been the rise of industrial policy following the global financial crisis. A study that identified which of more than 47,000 policy documents published between 2010 and 2022 were industrial policy documents found a thirty-fold increase in the number of such documents over the period (Juhász et al., 2025). For a long time, the primary objective of industrial policy was essentially to promote structural transformation by supporting manufacturing. Today, however, it encompasses a broad range of objectives, including accelerating the transition to net zero, mitigating the effects of climate change, strengthening supply-chain resilience, achieving strategic autonomy and competitiveness in key sectors and enhancing national security (Evenett et al., 2024). Strategic competitiveness is the most frequently stated objective in industrial policy documents, while mitigating the effects of climate change is the second most frequently cited objective. Emerging industrial policies in advanced economies target predominantly high- and medium-high-tech manufacturing and the energy sector, while in emerging market and developing economies, low-tech manufacturing is also prominent alongside these sectors (IMF, 2025).

Of the industrial policies announced between 2015 and 2024, 49% consisted of selective poli-

cy interventions targeting firms. China led on the basis of the share of selective industrial policy interventions (87%), followed by the United States (66%) and the European Union (61%). Firm-specific incentives in advanced economies and China have been largely directed toward strategic sectors such as semiconductors, advanced technologies, clean energy and critical minerals, whereas in developing countries, the vast majority of selective incentives are directed toward more traditional sectors such as agriculture, food processing, oil, natural gas and electricity generation (UNCTAD, 2026).

In Türkiye, industrial policies have also increasingly prioritized technology development since 2019. For example, the Technology-Oriented Industry Move Program, launched in 2019 under the 2023 Industry and Technology Strategy, continues under the name Technology Move Program as a component of the New Incentive System (NIS), which entered effect in 2025. The program, which focuses on priority products in medium-high and high-tech sectors, such as machinery, chemicals, electrical equipment, motor vehicles, pharmaceuticals and medical devices, computers, electronics and optical products, provides R&D and investment support to encourage domestic production. Another component of the NIS, the Strategic Move Program, aims to support strategic investments with high technological content, including the production of advanced-technology machinery, active pharmaceutical ingredients and semiconductors, as well as R&D-intensive strategic investments related to the green and digital transitions. The HIT-30 High Technology Investment Program, launched in 2024, provides project-based incentives for investments in seven technological areas—semiconductors, mobility, green energy, advanced manufacturing, healthy living, digital technologies and communications and space—as well as complementary investments for value chains in these areas (STB, 2025). As can be seen, a broad group of technologies, including digital technologies, lies at the heart of Türkiye’s industrial policies. In addition, the defense industry, which has notched up an impressive performance in both production and exports over the past two decades, has increasingly begun to influence industrial policy. The 2030 Industry and Technology Strategy aims to cast the achievements of the defense industry as a role model for other sectors and to support the domestic production of advanced-technology products in priority sectors such as pharmaceuticals and medical devices, rail systems and cybersecurity by using long-term planning, effective coordination, and public procurement—which are considered to have contributed to the achievements of the defense industry—as levers (STB, 2025).

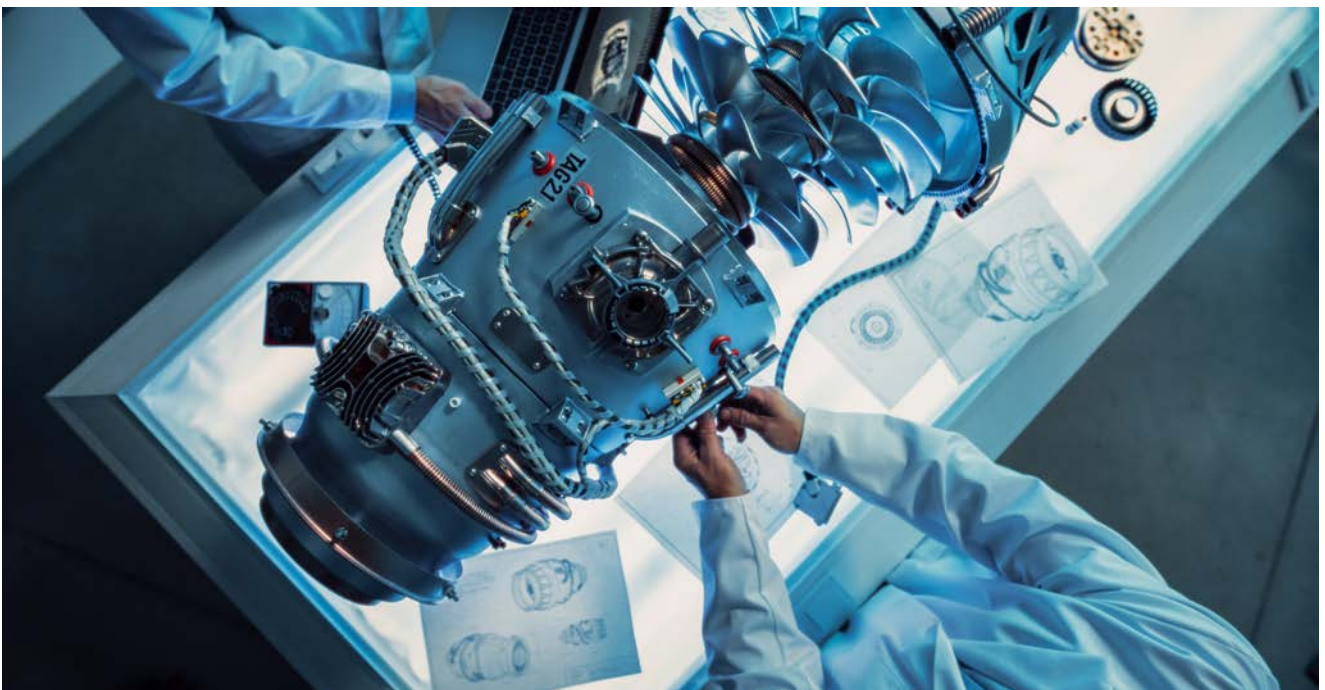
Demographic Transformation

Declining fertility rates and increasing life expectancy have led to ageing populations in many

countries, accompanied by a rise in old-age dependency ratios, along with a decline in the working-age population as populations age. In the OECD, as the share of workers in the population declines, the rate of growth in per capita income is projected to fall from its 2006–2019 average of 1.0% to 0.6% in 2024–2060, assuming average labor productivity growth of 0.7% (OECD, 2025). At the same time, rising old-age dependency ratios will increase the share of healthcare and pension expenditures in GDP, creating additional pressure on growth in per capita income. Upper-middle income countries, such as Türkiye, will age more rapidly and reach the same old-age dependency ratio at a lower level of per capita income than high-income countries (Tur, 2026). In view of the pressure that demographic transformation will place on growth and public expenditures, technological transformation is additionally important.

The Scope of Technological Transformation

The term “technology,” which we frequently use, essentially refers to a tool, piece of equipment, process, or product/service which we use to achieve a specific purpose. Technology, in these various forms, is not a monolithic entity. Technologies have a modular and recursive structure (Arthur, 2009). When we refer to an aircraft, for example, we are referring to all of its components, such as avionics systems, jet engines, and the fuselage and wings made of composite materials. Each of these subcomponents is itself a technology and they in turn consist of further technologies. Moreover, technologies always rely on a particular natural phenomenon or effect as their operating principle.



Technological progress has played a major role in the sustained economic growth experienced over the past two centuries. Technological progress takes two basic forms. Existing technologies can be gradually refined to reduce costs, lower energy and raw material requirements or increase performance and durability. Such changes may be referred to as micro-inventions or minor technological change. Technologies based on a new principle or idea and representing major leaps, on the other hand, may be referred to as macro-inventions or major technological change (Mokyr, 1990). The incremental improvements underlying micro-inventions may unfold over long periods of time, and the resulting cumulative improvements may pave the way for significant productivity gains both in the production of the relevant technology and in the other production processes in which that technology is used. However, incremental improvements eventually reach a limit with their further contribution to growth becoming negligible. The emergence of macro-inventions gives rise to new firms and industries. The resulting increases in production fuel economic growth, giving rise to opportunities for further incremental improvements.

Micro-inventions generally emerge from deliberate efforts to seek improvements and respond to market forces such as demand, prices, profits and competition. Although factors such as individual ability, inspiration, and chance play an important role in the emergence of macro-inventions, those that can be considered radical technologies have increasingly depended on high levels of R&D expenditure. Most radical technologies have also relied on publicly funded R&D expenditure (Mazzucato, 2013; Ruttan, 2006).

Moreover, technologies are interconnected and emerge in conjunction with other technologies. Technologies which serve as inputs to a particular technology, as well as other technologies and production activities using it, are also interconnected, thus forming a technology system (Perez, 2010). Similarly, technology systems also emerge in relation to one another. Clusters of interconnected radical innovations are referred to as technological (industrial) revolutions. There have been five industrial revolutions since the first Industrial Revolution which started in Great Britain in the second half of the eighteenth century. The radical digital technologies which define the ICT revolution, which emerged in the 1970s and are regarded as the fifth industrial revolution—including computers, chips, software, and telecommunications equipment and services—constitute the core digital economy (Barefoot et al., 2018). Economies are becoming digitalized as these technologies are used in existing economic activities on the one hand and play a fundamental role in the emergence of new economic activities on the other (Bukht & Heeks, 2017). The ICT technological revolution and the digitalization it has given rise to are now gaining new momentum with the emergence of various

technologies grouped under the umbrella of AI.

One component of the twin transition, a concept first used in European Union (EU) policy documents, is the digital transition (or digitalization), which began roughly 50 years ago and has recently been energized by AI. The other component of the twin transition, the green transition, refers to a transformation aimed primarily at achieving net zero by reducing the energy system's dependence on fossil fuels, improving energy efficiency in production and consumption, reducing environmentally harmful waste, protecting biodiversity, adopting more sustainable agricultural practices, and increasing circularity in production and consumption. It is not possible to achieve all of these objectives, which are at the core of the European Green Deal adopted by the EU in 2020, in a world where producers and consumers continue to rely on existing technologies. While digitalization clearly has the potential to provide a significant contribution to more efficient resource use and environmental protection (Avcioğlu, 2021), the fundamental objectives of the green transition obviously cannot be achieved solely by taking advantage of the opportunities offered by ICT. The green transition therefore itself necessitates a process of creative destruction that requires a replacement of the traditional technologies underpinning existing production and consumption practices by a large number of new technologies. In other words, the green transition is itself a technological transformation. Radical technologies—or what Mokyr refers to as macro-inventions—such as solar panels, wind turbines, batteries, electric vehicles, heat pumps and electric boilers, provide good examples of the technological dimension of the green transition. Although the first uses of technologies such as solar panels and wind turbines date back to the 1970s, their widespread adoption has taken place over the past



two decades. Thus, another technological transformation that has been underway for at least 20 years is unfolding within the broader ICT technological revolution.

Advanced and emerging technologies with strong transformative potential which offer new opportunities for economic development, sustainability, and governance are referred to as frontier technologies (UNCTAD, 2018). Both the increase in patent applications and significant changes in prices and quality reflect the rapid development of these technologies. Since 2018, the United Nations Conference on Trade and Development (UNCTAD), which has been monitoring frontier tech-

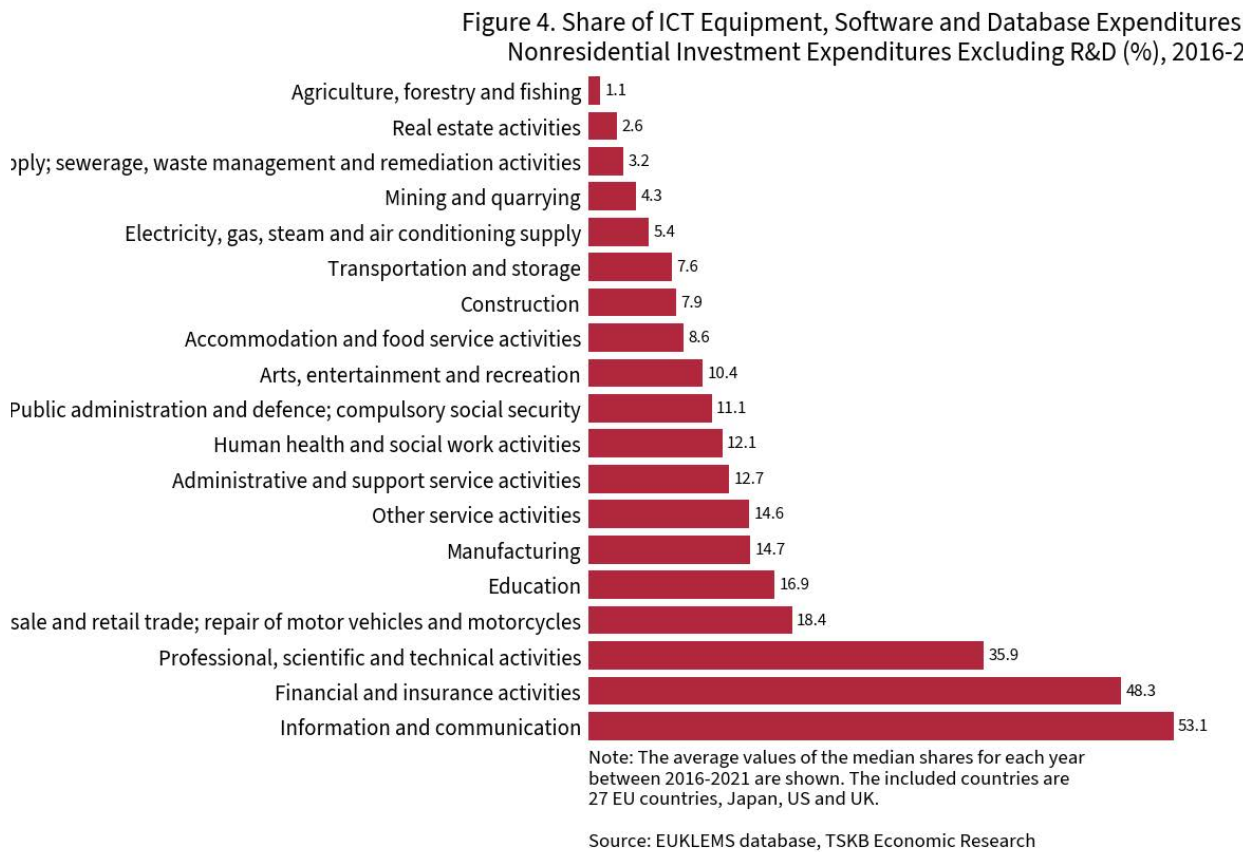
nologies, has classified 17 frontier technologies into three broad groups: (a) Industry 4.0 technologies, (b) green and renewable energy technologies and (c) other technologies (UNCTAD, 2025). There are three noteworthy features of this classification. All technologies in the Industry 4.0 group are either fully or partially digital (e.g., drones and robots). The vast majority of green and renewable energy technologies are technologies that enable energy production from renewable sources. The “other technologies” group includes two specific technologies from the biotechnology and advanced materials technology clusters.

Although frontier technologies bring together advanced and emerging technologies from different technological and scientific fields, this classification does not fully reflect the existing diversity of technologies and does not sufficiently cover the areas in which technological progress needs to take place, or is desirable, in the context of the green transition. For example, new equipment and processes required for decarbonization and resource efficiency in basic input producing sectors such as iron and steel, aluminum, cement, chemicals, plastics, and fertilizers are not included in this classification. Likewise, it does not include many specialized machines, equipment and inputs used in industry that are not entirely digital. Although these latter technologies may not be subject to rapid technological improvements, they remain essential intermediate and capital goods for industry.

A better understanding of this could be gained by examining how the use of core digital technologies varies across economic activities. For example, investment in ICT equipment, software, and databases accounts for around 50% of total investment expenditure excluding construction and R&D in information and communication and financial and insurance activities, while the share is significantly lower in agriculture, energy and manufacturing (Figure 4). The main reason for the relatively low share in agricultural and industrial activities is that these activities rely on a much broader range of capital goods.

We noted that technological revolutions, which play an important role in the continuity and fluctuations of economic growth, consist of a set of new technologies. While the emergence of new technologies may lead to the disappearance of some existing technologies, this does not mean that all older technologies necessarily become obsolete. For example, although steel and electricity, which have been the defining technologies of the third technological revolution, have lost their role as the primary drivers of growth, they have not lost their fundamental function in the economy. The continued competitive production of many technologies that emerged during earlier technological revolutions therefore remains important, particularly in the industrialization strategies of developing countries. In other words, particularly in developing countries, industrial and technology policies

should not focus solely on frontier technologies but should also take into account a broader range of technologies that are essential to economic activities, especially agriculture and industry.



It is also important to consider how the technologies at the heart of technological revolutions emerge. Defense procurement and R&D expenditure in the United States played an important role in the emergence of computers and the internet, for example (Mowery, 2010). Moreover, since the first Industrial Revolution, scientific advances have increasingly contributed to the emergence of new technologies. Therefore, well-designed science, technology, and industrial policies should be prioritized to achieve a technological transformation centered on both new and existing technologies. These policies should specifically target the development of green technologies, which have a critical role to play in an ecosystem-friendly transformation.

These observations can be summarized as follows:

- The ICT technological revolution and digitalization process that began in the 1970s still continues to this day.
- AI is initiating a new wave of digitalization.
- Although there is synergy between green and digital technologies, the green transition inherently encompasses a technological transformation that extends beyond digitalization.

- The technological dimension of the green transition places it as one of the main areas of focus for science and technology policy.
- Some “old” technologies continue to perform fundamental functions in the economy and remain important for industrialization.

Therefore, technological transformation encompasses the broad technological universe consisting of digital, green and other technologies. The transformation of industry should likewise be managed with this broader technological universe in mind.

Artificial Intelligence as a Radical Technology

The launch of OpenAI’s generative artificial intelligence (GenAI) chatbot, ChatGPT, in November 2022 marked the beginning of a new era. This chatbot uses a large language model called GPT, based on an artificial neural network architecture, to generate text, speech and images in response to user prompts. Meta launched its LLaMA large language model in February 2023, Anthropic released Claude in March 2023, and Google launched Gemini in November 2023. In the United States, the adoption rate of GenAI reached 39.4% in just two years, including both workplace and household use. By comparison, the adoption rates of the internet and computers had only reached around 20% three years after their introduction (Bick et al., 2024). Later, Chinese startups such as DeepSeek, Moonshot AI, and z.AI released models with capabilities relatively close to those of US-based models. Thus, as the number of GenAI models continued to increase, their adoption also expanded at an unprecedented pace. The widespread use of these increasingly capable GenAI tools has fueled concerns over the potential negative effects of AI on jobs.

With the widespread use of GenAI tools, the many techniques and applications which can be classified under AI are remaining in the background. The concentration of data center investment in a small number of countries further reinforces this perception. First and foremost, how should we define AI?

What Do We Mean by Artificial Intelligence?

The OECD played a leading role in 2019 by adopting an international standard on AI (OECD, 2019). The “Recommendation on Artificial Intelligence” also proposed a definition of AI. According to the OECD, “an AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations,

or decisions that can influence physical or virtual environments” (OECD, 2024). Inputs, models and outputs are the three components of an AI system. Inputs consist of data such as numbers, text, images, rules, and code, while outputs fall into broad categories such as recommendations, predictions and decisions and reflect the tasks performed by AI systems. Models, the core component of AI systems, are physical, mathematical or logical structures that perform inference to generate outputs from inputs. Because AI systems must be developed before they can be deployed, the phrase “infers ... how to generate outputs” in the definition highlights the model-building stage of AI system development. AI systems may operate at different levels of autonomy and can adapt by using inputs from the environments in which they operate.

AI models rely on techniques which draw on machine learning and knowledge-based (symbolic AI) approaches. However, one of the turning points in the development of AI was the emergence of applications based on artificial neural networks. Although the research underlying artificial neural networks dates back to the 1980s, the development of applications capable of producing meaningful results required advances in computer hardware, such as chips. While artificial neural networks have been decisive in the success of large language models, the use of these techniques goes beyond GenAI applications. For example, systems referred to as physical AI—including cameras, industrial robots, humanoid robots, and autonomous vehicles—can use AI to perceive the physical world and autonomously reach decisions and take actions which can alter their physical environment (Nvidia, n.d.). Both these systems and solutions based on other AI techniques are paving the way for greater use of AI in economic activity such as manufacturing, energy, transportation and agriculture.

The concept of general-purpose technology (GPT) is used to classify technologies which have deeper and more far-reaching effects than other technologies. A technology or a group of technolo-



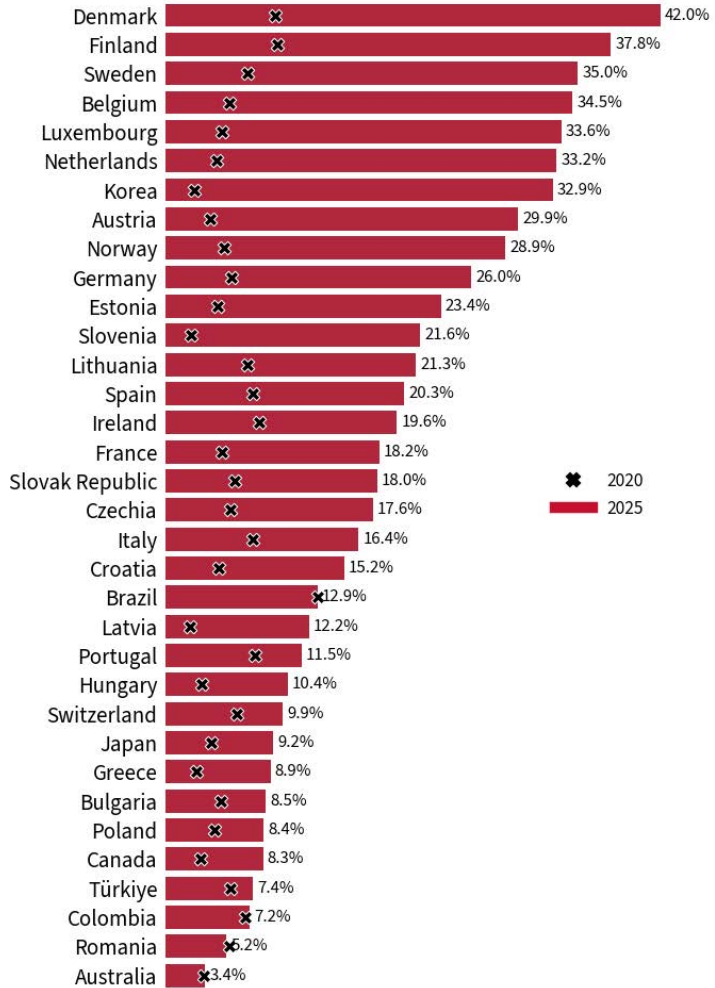
gies can be considered a general-purpose technology if it is used across a wide range of economic activities, undergoes continuous improvement over time and enables innovation in products and processes. Steam engines, electricity, chips, computers and the internet are important examples of general-purpose technologies. AI can also be regarded as a general-purpose technology because it has the potential to generate all three of these effects. Some authors go further and argue that GenAI itself is a general-purpose technology (Calvino et al., 2025). General-purpose technologies can potentially eventually generate significant waves of productivity growth and improvements in living standards. This characteristic is one reason why many countries regard AI as a strategic technology.

The Adoption of AI and Its Impact on Productivity

Between 2020 and 2025, the share of businesses using AI increased significantly in most OECD countries, while the AI adoption rate in Türkiye remained limited at 7.4% (Figure 5). At the same time, it is important to bear in mind that the AI adoption rate is not a sufficiently precise statistic; for example, it provides no information concerning the areas in which AI is used or how intensively it is used.

A study combining ICT survey data from 15 OECD countries with balance-sheet and employer-employee data provides important findings on how AI adoption varies across economic activities, the factors that may influence its adoption and the impact of AI on productivity (Calvino et al., 2026). In almost all countries, the ICT sector stands out as the sector with the highest AI adoption. The professional and scientific activities sector is the second-largest user of AI in many countries. By contrast, manufacturing and energy come with significantly lower AI adoption rates. While AI adoption increases in parallel with firm size, in countries such

Figure 5: Share of Enterprises Using AI (2020 vs. 2025, OECD countries)



Note: For Ireland, 2020 value is used for 2021. Israel, United Kingdom and New Zealand are not shown due to missing data and USA due to time series break.

Source: OECD Going Digital Toolkit, TSKB Economic Research

as Belgium, Canada, Germany, the United Kingdom, and Japan, the divergence begins among firms with 50 or more employees. This finding suggests that scale provides an advantage in the adoption of AI technologies. The study also found that human capital and other digital technologies are important determinants of AI adoption. The presence of ICT specialists and other employees with ICT training increases AI adoption. Likewise, AI adoption increases as the use of digital technologies such as robotics, big data analytics, 3D printing, the Internet of Things, cloud computing, CRM, ERP, and e-commerce increases. This indicates that skills and digital capabilities play a complementary role in enabling AI adoption.

The study also finds that in most countries, firms using more AI are more productive than firms that do not use AI, although the magnitude of this relationship varies considerably across countries (for example, the coefficient is 7.7% in France and as high as 31% in Belgium). More importantly, the productivity gain associated with AI adoption declines substantially when ICT skills and the use of other technologies are controlled for. Specifically, among the 10 countries where firms using AI appear to be more productive, only two show evidence that the productivity gain is actually attributable to AI, while ICT skills and other digital technologies are associated with higher productivity in all countries. As the study points out, this finding can be interpreted as suggesting that AI is not, by itself, a driver of productivity growth and that benefiting from AI is conditional on digitalization.

AI and Employment

In assessing the impact of technology on jobs, it would be more instructive to focus on the tasks that make up jobs. New technologies can affect jobs by either substituting for or complementing labor in some of the tasks that constitute them. These two premises play a central role in research on how GenAI will affect jobs. By employing a range of methodologies, researchers generally seek to establish a quantitative relationship between AI, and GenAI technologies in particular, and tasks, and to measure the extent to which this relationship is substitutive or complementary. They then use (un)employment statistics for jobs or occupations to examine the relationship between AI and (un)employment.

Gmyrek et al. (2025) determines the extent to which each task comprising a job could be automated by GPT-like technology and groups occupations by calculating the mean and standard deviation of their task-level automation scores. Occupations with a relatively low mean automation score and high standard deviation are placed in Group 1. Although some tasks in these occupations have high automation scores, the low scores of other tasks implies a greater role for humans in these

occupations. Accordingly, the augmentation effect of GenAI can be considered to be stronger for these occupations. Occupations with the highest mean automation score and the lowest standard deviation are placed in Group 4. A high mean automation score combined with low variation in task-level automation scores implies that these occupations have the highest automation risk. These are the occupations most exposed to GenAI. Thus, moving from Group 1 to Group 4 implies a decline in the augmentation effect but an increase in the automation risk.

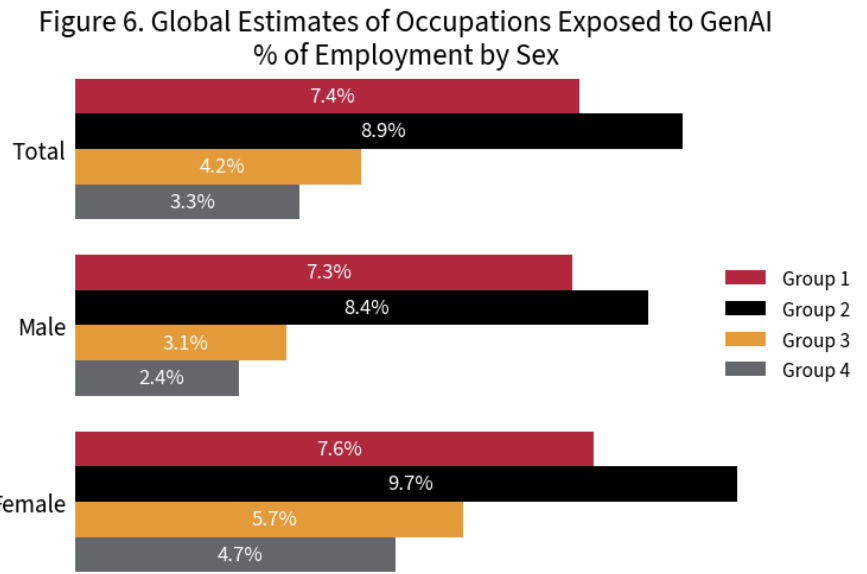
Eight of 13 occupations in Group 4 which have the highest automation risk due to GenAI belong to the occupational group of clerical support workers. Overall, these occupations are predominantly knowledge-intensive jobs performed in office environments.

Figure 6 shows the share of employment in 112 occupations exposed to GenAI (Groups 1–4) in total employment for the global economy. Approximately 24% of global employment is exposed to GenAI. However, the share of female employment exposed to GenAI is higher than for male employment (28% compared with 21%). In high-income countries, 34% of total employment is exposed to GenAI, with the share rising to 41% among women, compared with 28% among men. In general,

the share of employment exposed to GenAI decreases as income levels decline across country groups. The main reason why a higher share of total employment—and particularly female employment—in high-income countries is exposed to GenAI is that occupations such as clerical

and financial jobs and customer services, which are among those most exposed to GenAI, are more prevalent in high-income countries and have a higher share of female workers.

Another important finding is that the share of jobs in Group 4, which has the highest automation risk, is relatively small. These jobs account for 3.3% of total employment, compared with 4.7% of female employment and 2.4% of male employment. Although these shares are higher in high-income countries, the overall share of such jobs is still just 6.3% of total employment.



Source: Gmyrek et al. (2025)

Estimates of exposure to AI vary substantially across studies. For example, another study focusing on AI rather than GenAI and using 2024 data, finds the share of employment in highly AI-exposed occupations to be 60% in high-income countries, 40% in emerging market economies and globally, and 41% in Türkiye. The same study finds that the share of routine and automatable jobs in Türkiye which are highly exposed to AI and in which the use of AI could substitute workers in performing tasks is 18.7%. In terms of economic activities, these jobs are particularly concentrated in information and communication, wholesale and retail trade and professional services; by occupational group, they are concentrated among service and sales workers and clerical support workers (Aşık et al., 2026).

As the studies emphasize, these estimates do not reflect the actual impact of GenAI on employment; rather, they indicate exposure to GenAI. They should also be regarded as estimates for the upper boundary of the share of jobs that could potentially be affected by GenAI. Factors such as infrastructure constraints, shortages of digital skills, the cost of technology and limited productivity gains may prevent the full adoption of GenAI and limit its impact on employment.

Another study focusing on the US economy, using monthly occupational employment data between January 2021 and September 2025, suggests that the impact of AI may differ across age groups (Brynjolfsson et al., 2025). According to the study, employment among young workers aged 22–25 declined significantly after 2022 in occupations such as customer service representatives and software developers, which are highly exposed to GenAI. By contrast, there was an increase in employment among older workers in the same occupations and among workers of all age groups in jobs less exposed to AI. One of the study's key findings is that this decline is more likely to have been



caused by GenAI than by factors affecting firms or industries in the same way. Employment among young workers aged 22–25 in the two quintiles of occupations most exposed to GenAI exhibited a decline relative to employment among young workers in the least exposed quintile. However, this decline began to emerge only from 2024 (Smith, 2026). No comparable relative decline was observed among other age groups.

The finding that both the decline in youth employment in occupations most exposed to GenAI began after the end of 2022 and the portion of this decline that may be associated with GenAI emerged only from 2024 onward suggests that other factors may also have contributed to the decline in youth employment. Another study focusing on the United States, combining unemployment insurance records with LinkedIn job postings, found a rise in the risk of unemployment in occupations exposed to GenAI in early 2022. It also found a lower rate of new graduates entering exposed to GenAI starting in 2021 when compared to earlier periods, with the gap emerging before the end of 2022 (Frank et al., 2026).

Table 1. 10 Occupations Most Exposed to GenAI	
Computer programmers	74.5%
Customer service representatives	70.1%
Data entry keyers	67.1%
Medical record specialists	66.7%
Market research analysts and marketing specialists	64.8%
Sales representatives, wholesale and manufacturing, except technical and scientific products	62.8%
Financial and investment analysts	57.2%
Software quality assurance analysts and testers	51.9%
Information security analysts	48.6%
Customer user support specialists	46.8%
Source: Massenkoff & McCrory (2026)	

Studies attempting to quantify the extent to which tasks are exposed to GenAI may be regarded as assigning upper-bound values. In other words, due to the complexity encountered in actual work processes, real-world exposure to AI is likely to be lower than the theoretical estimates. Building on this premise, another study focuses on which tasks that large language models could theoretically accelerate are actually being used for job automation and measures observed exposure (Massenkoff & McCrory, 2026). The study finds a striking gap between theoretical potential and observed exposure. At the occupational level, computer programmers (74.5%), customer service representatives (70.1%) and data-entry keyers (67.1%) are among the occupations with the highest expo-

sure to GenAI (Table 1). To assess the employment effects of GenAI, the study also compares unemployment rates between workers in occupations with the highest exposure to GenAI and workers in occupations with the lowest exposure. It finds that the difference in unemployment rates between the two groups did not change following the release of ChatGPT. However, the monthly job-finding rate for young workers aged 22–25 in occupations most exposed to GenAI was 14% lower than in 2022.

While these studies do indeed find that GenAI has negatively affected employment among workers aged 22–25 in occupations most exposed to the technology, other studies provide evidence that GenAI and youth unemployment are unrelated. For example, while the gap between the unemployment rate of university graduates aged 23–29 and the overall unemployment rate has been widening since 2016 in countries such as the United States, Canada and Australia, this increase has not accelerated since the end of 2022. Likewise, looking at the period beginning in late 2023, when the share of job postings mentioning AI began to surge in the United States, there was no significant difference between online junior job postings in occupations more exposed to GenAI and job postings in the least exposed occupations (OECD, 2026a).

Taken together, these findings suggest that GenAI has the potential to affect approximately one-fifth of global employment, while the share of jobs that could be automated is relatively small, at around 3.3%. Exposure to GenAI increases in parallel with the income level of each country. Women may be more affected by GenAI because of their higher representation in occupations most exposed to the technology, while youth employment in highly exposed occupations may also be negatively affected.

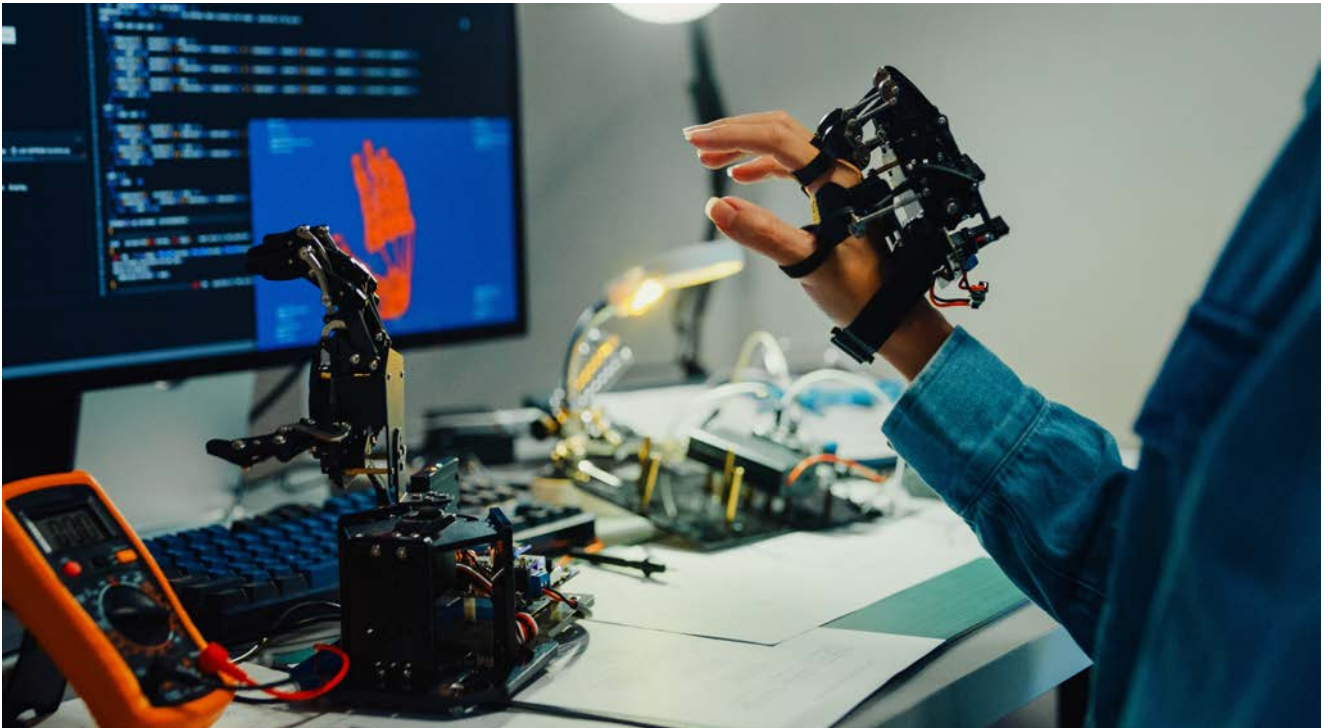
Preparing for the Future

A relatively recent and useful framework in assessing the impact of new technologies on jobs classifies technologies into three different groups by focusing on tasks: a) automation technologies which substitute capital for labor in some tasks, b) technologies that create new tasks, and c) factor-augmenting technologies (Acemoglu & Restrepo, 2018, 2019). Automation technologies reduce the number of tasks performed by labor and shift the distribution of tasks required for production toward capital. Technologies that create new tasks, by contrast, shift the distribution of tasks toward labor. For example, since 2019, occupations based on new tasks such as Internet of Things engineering technicians, AI engineering technicians, big-data engineering technicians and robotics engineering technicians have been added to China's National Occupational Classification System (Arias et al., 2025). Factor-augmenting technologies increase the productivity of labor or capital across all tasks

without changing the distribution of tasks in production.

Each technology increases productivity while encouraging the firms using the technology to produce more, in turn leading firms to employ more labor in tasks which can still only be performed by humans. However, there is a clear distinction between automation technologies and technologies that create new tasks. Since automation technologies eliminate some tasks and initially reduce demand for labor, their net effect on employment depends on the extent to which the increase in demand for labor resulting from productivity gains offsets this initial reduction. In contrast, the technologies creating new tasks increase demand for labor both through the creation of new tasks and through the productivity channel.

One missing element in discussions of AI's impact on employment is the extent to which AI will generate new tasks. Another revolves around the extent to which the productivity of AI applications leading to automation or augmentation will increase, and how much they will contribute to higher labor demand through this channel. However, there is considerable uncertainty surrounding these two critical questions, the outcomes of which will become clear in the future. Uncertainty also hangs over when the productivity gains potentially generated by AI will be reflected at the macroeconomic level, with such effects likely to be delayed. For example, although the first power plant in the United States was established in 1882, the widespread adoption of electricity in manufacturing and the resulting productivity gains did not emerge until the 1920s. Similarly, while the ICT revolution began in the 1970s, productivity gains did not emerge until the mid-1990s and proved relatively short-lived, ending by the mid-2000s (Gordon, 2016). Since AI is a digital technology, its effects are



less likely to emerge with a delay as long as in these historical examples; nevertheless, the duration of AI-driven productivity gains remains uncertain.

At the same time, as businesses more widely adopt AI, it would be reasonable to expect at least some of the jobs most exposed to AI to come under pressure through automation. In this case, the extent to which the productivity gains generated by these technologies have a compensating effect on employment will be crucial. However, job losses will inevitably occur when this compensating effect is insufficient. This raises the question of how skills policy should be designed as AI becomes increasingly widespread. In addition to basic ICT skills, acquiring advanced ICT skills—including the ability to understand and apply programming and AI algorithms—will facilitate both adaptation to changing jobs and continued learning. At the same time, metacognitive skills such as critical and creative thinking, the ability to learn and self-regulation and social and emotional skills such as empathy, responsibility and collaboration can play a complementary role. Policymakers therefore need to develop policies that help individuals acquire these capabilities and expand life-long learning and skills-development programs (OECD, 2026b).

Policies for Technological Transformation

Since the 2008 global financial crisis, industrial policy has been applied with increasing frequency in both advanced and developing economies. Moreover, in most countries, particularly advanced economies, industrial policy has increasingly focused on high- and medium-high-tech sectors and clean energy technologies. Countries pursuing industrial policies motivated by strategic competitiveness, climate change mitigation, resilience, national security and supply chain security are scrambling to avoid falling behind in the ongoing technological transformation.

Technology policies which can be classified as part of industrial policy focus directly on technology. Mission-oriented technology policy seeks to develop new and radical technologies in order to achieve nationally defined missions and gain international leadership (Ergas, 1986). However, developing radical technologies is neither the only way to advance technology nor does it guarantee the sustainability of competitiveness. Policies on technology may also prioritize expanding industry's capacity to adapt to technological transformation and promoting the broader use of existing advanced technological capabilities throughout the economy (Carlsson & Jacobsson, 1994; Ergas, 1986). Such policies are referred to as diffusion-oriented policies. Rather than creating entirely new products, diffusion-oriented policy focuses on micro-inventions involving incremental improve-

ments, as well as on increasing production efficiency and product quality (Chiang, 1991).

Diffusion-oriented technology policy relies on public or private institutions able to scan and monitor advanced technologies and facilitate their diffusion among firms. While it is relatively easy for large-scale firms to become aware of new technologies, this is considerably more difficult for the numerous smaller firms, particularly SMEs. Moreover, the scanning and monitoring in this context needs to be carried out in a timely manner. Sweden, for example, began adopting emerging factory automation technologies at an early stage, both through such institutions and through firms' ability to identify opportunities in a timely manner. Throughout the 1980s, Sweden became one of the countries with the most intensive use of technologies such as numerical-control machine tools, industrial robots, flexible manufacturing systems and computer-aided design, even though the country had not developed these technologies itself (Carlsson & Jacobsson, 1994). Similarly, in 2017, China identified AI as a strategic technology and published a policy document aimed both at developing the technology and promoting its use throughout the economy (DigiChina, 2017). China had previously also pursued diffusion-oriented policies aimed at expanding firms' adoption of technologies such as the internet and industrial robots (Güven, 2026).

Diffusion-oriented policies are an important component in the ongoing technological transformation in at least three areas. First, such policies seek to roll out technologies and practices which reduce carbon emissions, improve resource efficiency, reduce environmentally harmful waste and promote circularity across firms. Second, diffusion-oriented policies may facilitate the adoption of new technologies and production practices which extend beyond the basic set of digital technologies and are more widely used, particularly in manufacturing and agriculture. Third, they may support the wider use of AI applications in agriculture, manufacturing and services in order to benefit from the opportunities offered by AI, which represents the beginning of a new wave of digitalization. The digital nature of AI, together with the availability of open-source and open-weight models, indicate the considerable potential of strategies focused on expanding the use of AI. As the World Bank emphasizes, developing economies stand to benefit from the myriad of opportunities offered by AI by prioritizing its adoption and adaptation to their own circumstances (World Bank, 2026). Türkiye's Artificial Intelligence Action Plan likewise aims both to develop AI-based technologies and to widen the use of AI, particularly in industry and the public sector (STB, 2026).

New technologies which typically emerge in advanced economies typically follow in developing economies with a lag. Developing economies often begin producing these new technologies only after they have reached a certain level of maturity. As a result, they tend to catch up with technological revolutions with a delay, with production relying heavily on imitation. When it comes to the

green transition, however, developing economies do not need to wait for green and renewable energy technologies to mature, as they have done with previous technological revolutions (UNCTAD, 2023). In other words, developing economies are in a position to adopt an innovation policy based on directly developing green technologies, which can be referred to as green innovation, thus allowing them to



both pursue the green transition and derive greater benefits from the green growth driven by these technologies. Countries may encourage green innovation through well-designed industrial policies. Evidence suggests that those countries adopting an approach that goes beyond learning from leading countries in relatively new technologies have achieved success. Brazil, for example, has become a technology leader in biofuels, while China has emerged as a leader in solar panels. Both countries employed industrial policies to create strong domestic demand and invested in R&D and human capital (UNCTAD, 2023).

It is also important to recall that FDI plays an important role in technology transfer, supply chain integration and access to foreign markets. However, technological transformation, the rise of industrial policy, and geopolitical tensions are all affecting FDI. While the share of strategic sectors in greenfield investment is increasing, the share of other sectors is declining, partly as a result of the restructuring of global supply chains. Moreover, as advanced economies seek to attract international investment by committing greater resources, developing countries should, above all, establish strategic priorities and focus on a limited number of activities which can support structural transformation (UNCTAD, 2026). In addition, incentives provided under industrial policy should target technologies and activities which are relatively close to a country's existing capabilities while also offering the potential to generate structural transformation. For example, countries which host the critical minerals needed for technological transformation should go beyond mineral extraction and promote investments which establish higher-value-added refining, processing and materials production capabilities. Finally, prioritizing the infrastructure investments required by the green transition and the renewed momentum in digitalization with the increasingly widespread use of AI would not only

accelerate the technological transformation but also encourage FDI.

Technological Transformation as a Lever

Technological progress, the fundamental driver of long-term growth in per capita income, also creates significant opportunities for environmentally sustainable development. With the emergence of the new technologies at the heart of creative destruction comes a contraction in activities based on older technologies, the closure of some businesses and employment losses in certain occupations. Despite these challenges, new technologies support development by creating new areas of activity, supporting expansion in existing areas and facilitating the emergence of new jobs. By driving productivity growth, technological progress contributes to higher per capita income while also supporting an expansion in total employment by stimulating economic growth.

Green technologies, in turn, help ensure development is environmentally sustainable. Through decarbonization, the more efficient use of resources and steps to reduce waste, green technologies help protect the environment and restore ecosystems. Development banks also contribute to environmentally sustainable development by financing the development and diffusion of both green and other technologies.

Conclusion

The process of digitalization is ongoing with a combination of digital technologies and other technologies leading to the digitalization of a wide range of goods and services and the emergence of new economic activities based on digital technologies. However, technological transformation encompasses a transformation that goes beyond the broader adoption of core digital technologies throughout the economy. Green technologies, which largely consist of clean energy technologies, not only create synergies with digital technologies but also represent a technological renewal in their own right. Moreover, the intermediate inputs and capital goods, particularly those used in agriculture and manufacturing, rely on a much broader technological base than digital technologies. Developing these technologies therefore remains important for many developing countries, including Türkiye.

AI is revitalizing digitalization, but there is considerable concentration in the development of

AI models, the production of technologies such as chips and investment in AI infrastructure. Despite widespread concerns that AI, which is spreading more rapidly than computers and the internet, will lead to significant employment losses, the share of global employment that could be most affected by automation through GenAI appears to be relatively limited. There also remains considerable uncertainty regarding the time horizon and magnitude of AI's contribution to productivity growth and the number of new tasks and jobs that it will create. At the same time, AI may adversely affect certain occupations through automation, which appears to be placing a particular pressure on youth employment. Skills policies therefore need to focus on developing skills that incorporate digital capabilities and are aligned with the broader scope of technological transformation. Supporting youth and women's employment is also important for minimizing the risks faced by these groups.

The digital nature of AI and its emergence on top of previous waves of digitalization are facilitating its rapid diffusion. The increasing accessibility of open-source and open-weight models also offers significant opportunities, particularly for developing economies. However, easy access to AI does not mean that every firm is able to readily use the technology. Since technologies can have a meaningful impact on the economy only when they are widely adopted, designing and implementing diffusion-oriented policies to promote the adoption of AI in agriculture, manufacturing, energy and services will play a critical role in converting the potential of this technology into reality.

Diffusion-oriented policies that take the broad scope of technological transformation into account should also target technologies beyond AI. Identifying emerging advanced technologies and enabling firms to adopt them at an early stage can generate productivity gains and facilitate the development of higher-quality products. Diffusion-oriented policies could complement policies focused on developing radical technologies and contribute to technological progress based on incremental improvements. Mission-oriented policies should likewise focus on developing critical and strategic technologies, particularly green technologies.

Industrial policies are becoming increasingly prominent, while advanced economies are using substantially more resources than developing economies, particularly through incentives, to support domestic production of advanced technologies. This is also reflected in FDI. In such an environment, it is crucial that developing economies, whose financial resources are relatively limited, establish strategic priorities and pursue an FDI policy that promotes activities contributing to structural transformation, sustainability and resilience.

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