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The economic consequences of artificial intelligence : an overview

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The economic consequences of artificial intelligence: an overview*

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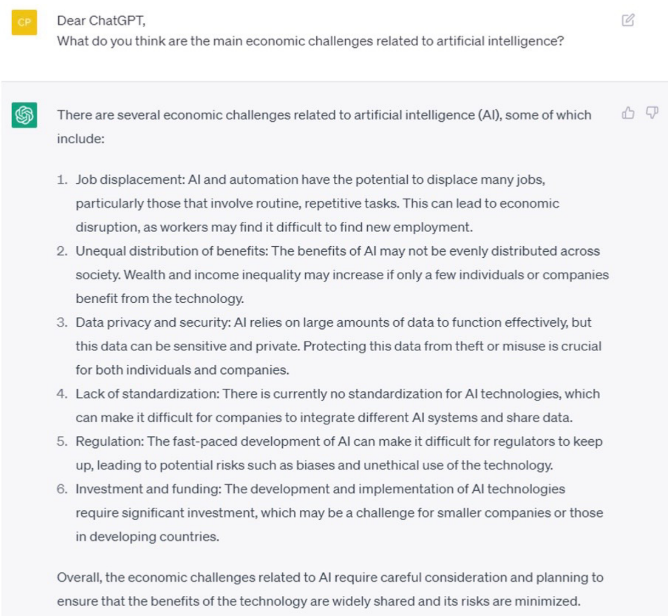
Introduction

Artificial Intelligence (AI) has developed rapidly in recent years and is having an increasingly important impact on our daily lives, in many areas. For example, voice assistants use AI to understand human speech and answer questions; online advertising for certain products is generated by algorithms analysing preferences; video and music platforms as well as social networks use AI to suggest content to suit customer preferences. AI can also be used in healthcare to improve diagnoses and treatment, in finance to detect fraud and manage risk, in transportation to optimise routes and reduce congestion, in manufacturing to improve quality control and efficiency, etc. These are but a few examples of the possible uses of artificial intelligence.

Figure 1

Sample of ChatGPT output



Source: OpenAI ChatGPT.

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Due to its broad array of applications, AI is considered a general-purpose technology (GPT), like for example the steam engine, electricity or the Internet. These technologies are characterised by their ability to be used across a wide range of industries and their capacity to generate long-term productivity growth and improvements in living standards. AI is a broad field encompassing a range of techniques and approaches to create tools that can perform tasks typically requiring human-level intelligence. These tasks can include image and speech recognition, natural language processing, decision-making and problem-solving.

The recent release of ChatGPT to the public in November 2022 propelled the issue of artificial intelligence to the top of economic and political agendas. Created by the Californian company OpenAI, ChatGPT allows users to enter a prompt and receive a unique, detailed response in a wide range of domains. The chatbot has already demonstrated its ability to pass a medical licensing exam (Gilson *et al.*, 2023), law school admission test (Choi *et al.*, 2023), a common assessment used in introductory physics courses (West, 2023), and micro- and macroeconomics tests (Geerling *et al.*, 2023). Figure 1 illustrates the output of ChatGPT when asked a simple question such as that posed in this article.

ChatGPT works with algorithms that process data, allowing it to string together words in response to a question. Unlike humans, ChatGPT can access vast amounts of information available on the Internet and uses language modelling to identify patterns in the words of a question to mimic human handwriting when dispensing knowledge. Although ChatGPT is a powerful tool, it does not "know" anything. It generates answers based on the probabilities assigned to individual words, which are calculated through an iterative training process involving large quantities of text.

AI has the potential to generate long-term productivity growth and improvements in living standards. By automating tasks that are currently performed by humans, AI could increase productivity and efficiency, freeing up workers to focus on tasks that require human-level skills such as creativity, judgment and interpersonal communication. However, the development and adoption of AI also raise important questions about its impact on the labour market, privacy and security as well as ethical considerations. As a result, the development of AI requires careful reflection and thoughtful policy and regulatory frameworks to ensure that its benefits can be realised while mitigating potential risks.

This article aims to identify the main challenges raised by artificial intelligence. Section 1 presents recent developments in AI. It defines what is meant by AI and provides some figures on its spread, especially amongst businesses. Section 2 looks at the impact of AI on productivity and growth. Although AI has the potential to increase productivity, its current impact, like other ICT developments, remains limited, leading to the so-called productivity puzzle or Solow paradox. Section 3 summarises how AI can affect the way companies operate, interact with each other, set prices, etc. As one of the risks associated with the use of AI is the replacement of certain workers or specific skills, Section 4 analyses in depth the potential consequences of AI on the labour market. Other risks are raised in the policy debate, particularly with regard to ethics and the harm caused by AI. Section 5 presents and discusses these other risks. Finally, the last section outlines the policies that will be needed in order to mitigate the risks and to benefit from AI's full potential.

1. The evolution of artificial intelligence

1.1 Definition of and recent developments in AI

There are multiple definitions of artificial intelligence, an overview of which is provided by Montagnier and Ek (2021). This array of definitions highlights the challenge of delineating AI, as it is not an isolated technology but rather an integrated component of ICT infrastructure and systems (such as software and hardware).

According to the *Oxford English Dictionary*, artificial intelligence or AI refers to "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages". AI itself, through ChatGPT, can also provide a definition: "Artificial intelligence (AI) refers to the ability of machines to perform tasks that would typically require human intelligence, such as recognizing speech, making decisions, and learning from experience. AI is achieved through the development of algorithms and models that can analyze and interpret complex data, and then make predictions or decisions based on that data. AI can be further divided into several subfields, including machine learning, natural language processing, computer vision, robotics, and expert systems. Each of these subfields focuses on a different aspect of AI, but they all share the common goal of creating machines that can perform tasks that would typically require human intelligence".

Nonetheless, analyses and quantitative research on AI, in particular cross-country comparisons, should be based on a common definition. For example, for its survey on ICT usage by firms, Eurostat defined AI as the set of technologies allowing: (1) the analysis of written language (text mining); (2) the conversion of spoken language into machine-readable format (speech recognition); (3) the generation of written or spoken language (natural language generation); (4) the identification of objects or persons based on images (image recognition, image processing); (5) the use of machine learning for data analysis; (6) the automation of different workflows or the provision of assistance in decision making (AI-based software, robotic process automation); or (7) the physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, self-driving vehicles, autonomous drones). It then determined that a firm relies on AI if it uses at least one of these technologies (see the next section for figures).

Despite the current popularity of ChatGPT, the majority of recent advances in AI have come from machine learning (Agrawal *et al.*, 2019). The development of machine intelligence became possible once researchers started to tackle intelligence tasks empirically rather than procedurally (Mullainathan and Spiess, 2017). Humans conduct many tasks that are not always codifiable. Face recognition is a good example. Algorithms that are able to recognise a face in a picture are not based on human understanding of what a face is. Instead, the program is trained on a large dataset of photos labelled as having a face or not and learns how to "recognise" a face by estimating a function predicting the presence of a face from certain pixels. Machine learning has therefore been a success due to its ability to discover complex structures that were not specified in advance. In other words, rather than define specific rules, program designers let the data tell the program which rules work best.

Machine learning is a powerful tool for improving predictions, a key element in decision-making processes. This type of forecasting is useful in many areas (Kleinberg *et al.*, 2015). For example, it can be used in the labour market to determine the expected duration of periods of unemployment and prioritise job seekers for support, in social policy to target the most at-risk young people (Chandler *et al.*, 2011), in education to predict which teacher will have the most value added (Rockoff *et al.*, 2011), or in the financial sector to determine potential borrower creditworthiness. It therefore has the potential to have widespread consequences in a wide range of sectors (Brynjolfsson *et al.*, 2018b). Considered a general-purpose technology (GPT), artificial intelligence, including machine learning, will have implications throughout the economy, for all agents, activities and geographical areas.

1.2 Some statistics on the development of AI

Worldwide, private investment in artificial intelligence doubled between 2020 and 2021. The Stanford Institute for Human-Centered Artificial Intelligence currently estimates it at around $ 93.5 billion. The number of patents filed in recent years is also evidence of the rapid progress being made in this field. In 2021, this figure was more than 30 times higher than in 2015. The historical leading country in AI is the US but China has been rapidly catching up. The US has an advantage in terms of private investment and the number of newly funded companies. China leads in the number of AI-related journal publications, conferences and data repositories. In general, many countries have reported an increase in AI-related recruitment and hiring.

Europe is generally considered to be lagging behind the US in terms of the development and adoption of AI. The US has a larger and more established tech industry, with major companies such as Google, Amazon and Facebook leading the way in AI research and development. Additionally, the US has a well-established ecosystem of venture capital and start-up funding, which has helped to fuel the growth of innovative AI companies. However, Europe has been making significant efforts to catch up in the field of AI. Several European countries are particularly active in AI research and development, such as the United Kingdom, France, Germany and the Nordic countries. These countries have invested heavily in AI research and have adopted measures to promote the development and adoption of AI. Moreover, the European Union has launched a number of initiatives to further AI, such as the European AI Alliance and the European AI Fund. The EU is also working on a comprehensive AI strategy with the goal of becoming a global leader in AI while ensuring that the technology is developed and used in an ethical and responsible way.

While Belgium may not be the first country that springs to mind when thinking about the development of AI, it is making significant efforts to establish itself as a major player in the field. It is also a leading country in terms of innovation and research and development. Whether it's research centres, funding for start-ups, educational programmes or industry events, Belgium is taking steps to promote the growth of its AI industry. Examples include AI4Belgium at national level, the FARI Institute in Brussels, DigitalWallonia4AI in Wallonia and the FAIR research centre in Flanders. In order to bring together the various national and federated initiatives, Belgium adopted a National Convergence Plan for the Development of Artificial Intelligence in October. The plan proposes nine concrete objectives to make Belgium a #SmartAINation. These include strengthening the country's competitiveness and attractiveness, acquiring the necessary skills for the population, and cybersecurity.

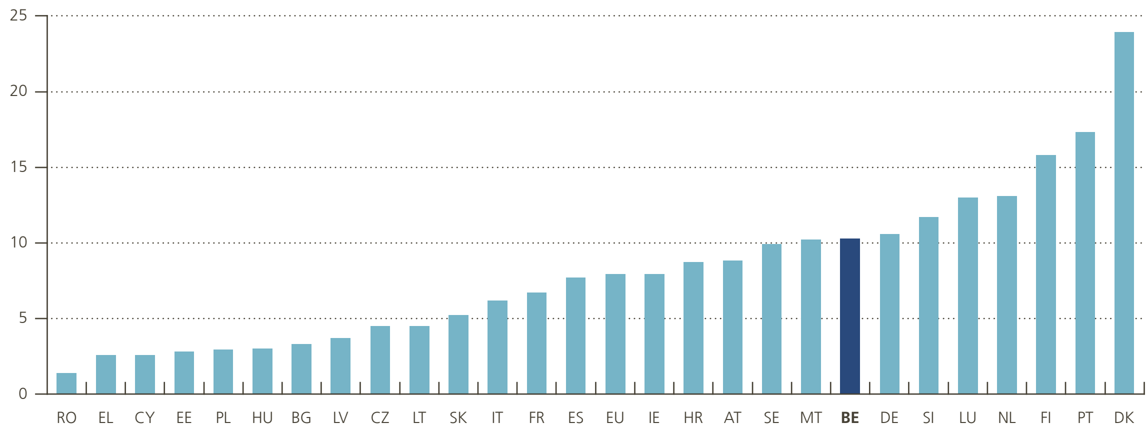
With regard to AI diffusion amongst firms, Belgium is ranked 8th in the EU, with slightly more than 10 % of businesses using at least one AI technology. This percentage is far behind that of the best performer, Denmark, with 24 %, but is still above the European average of 8 %.

Of the reasons indicated by firms for using AI, ICT security was cited most often, followed by the organisation of business administration and production processes. Other reasons mentioned, but less often, were management, marketing and sales, logistics, and human resources management and recruiting. To improve the diffusion of AI,

Figure 2

Firms using at least one AI technology [1]

(in %, 10 employees or more, all activities except the financial sector, 2021)



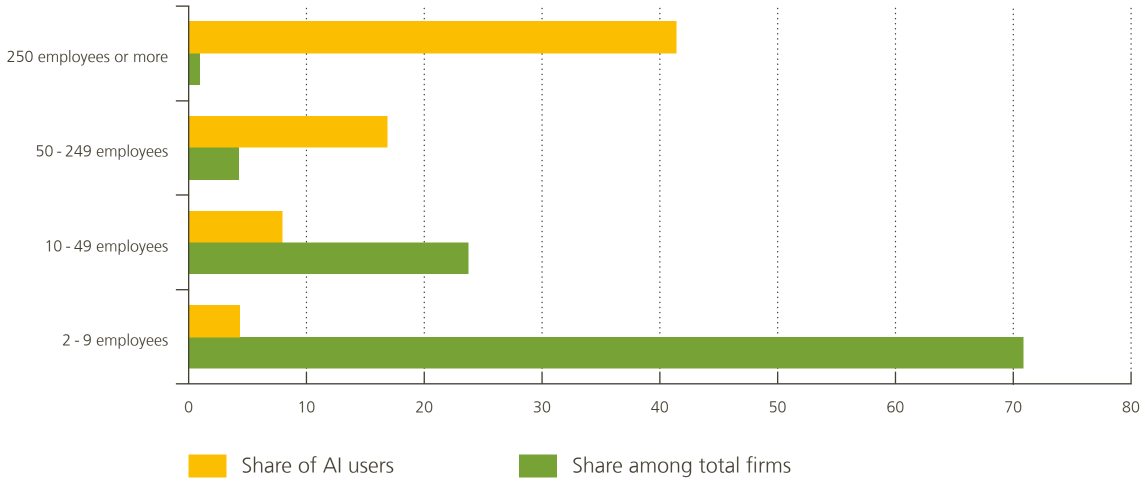
Source : Eurostat.

1 AI technologies include text mining, speech recognition, natural language generation, image recognition and processing, machine learning, AI-based software robotic process automation, autonomous robots, self-driving vehicles and autonomous drones.

Figure 3

Firms using at least one AI technology[1], by size

(in %, all activities except the financial sector, 2021)



Sources: Statbel and NBB calculations.

1 AI technologies include text mining, speech recognition, natural language generation, image recognition and processing, machine learning, AI based software robotic process automation, autonomous robots, self-driving vehicles and autonomous drones.

it is important to understand the obstacles faced by firms when adopting AI. According to a Statbel survey, lack of relevant expertise is the main barrier to the adoption of AI technologies. Incompatibilities with existing equipment, software or systems, too-high costs and poor availability or quality of data were also cited by respondents. Legal and ethical aspects were mentioned but were at the bottom of the list. Finally, only a very small share of firms think that AI technologies are not useful for their business. These findings are not unique to Belgium. Lane *et al.* (2023), who surveyed more than 2 000 firms in seven OECD countries, noted that employers consider cost and lack of skills to be greater barriers to AI adoption than government regulation.

While AI could influence many sectors, the share of firms in Belgium using at least one AI technology is the highest in the information and communication sector (34.8 %), followed by professional, scientific and technical activities (20.2 %) and manufacturing (10.4 %).[1] The same sectors emerge in other OECD countries.

As illustrated in Figure 3, the use of AI amongst firms also varies depending on the size of the company. While large firms, with 250 employees or more, represent only 1 % of total firms in Belgium, 41 % of them use at least one AI technology. For very small companies, with two to nine employees, the survey indicated that only 4 % have adopted AI. Economies of scale related to the cost of using AI and the need for additional investment, notably in ICT and skills, explain the more widespread use of AI by large companies. Moreover, the firms more likely to use AI are those which are more digitalised (Calvino and Fontanelli, 2023). This finding is in line with Brynjolfsson *et al.* (2021) who pointed out the existence of complementarities between the adoption of AI by a firm and its overall level of digitalisation. A digitalised company will face fewer barriers when adopting AI since it has already developed a series of complementary assets, such as internal digital business capabilities or the acquisition of large datasets.

Statbel's survey on the use of AI by firms also revealed regional disparities. The largest share of firms using AI can be found in Brussels, with 15 %. In Flanders, 11 % of firms use at least one technology considered AI, while in

1 It should be noted that the financial sector was not covered by Statbel's survey but is known to be one in which the use of AI is particularly high.

Wallonia this share is only 7 %. Analysing digital technologies in a more general way, Goldfarb and Tucker (2019) suggest that the biggest beneficiaries are in large urban areas. Forman *et al.* (2005, 2008) discovered that the use of the Internet by businesses is more prevalent in both metropolitan areas and large firms. However, they also observed that the benefits associated with being based in a city or with a large firm are interchangeable, indicating the significance of agglomeration effects. Dranove *et al.* (2014) made comparable findings with regard to hospitals.

2. The impact of artificial intelligence on productivity

AI has the potential to significantly impact productivity growth in a variety of industries. In manufacturing, for example, AI-powered robots and automation can increase production efficiency and reduce the need for human labour. In the services sector, AI-powered chatbots and virtual assistants can handle routine tasks and free up human employees to focus on more complex, high-value work. In addition, AI-driven analysis of big data can help companies make more informed business decisions, leading to increased productivity and growth. Finally, Aghion *et al.* (2018) demonstrate that AI is an input in the production of ideas and therefore stimulates innovation.

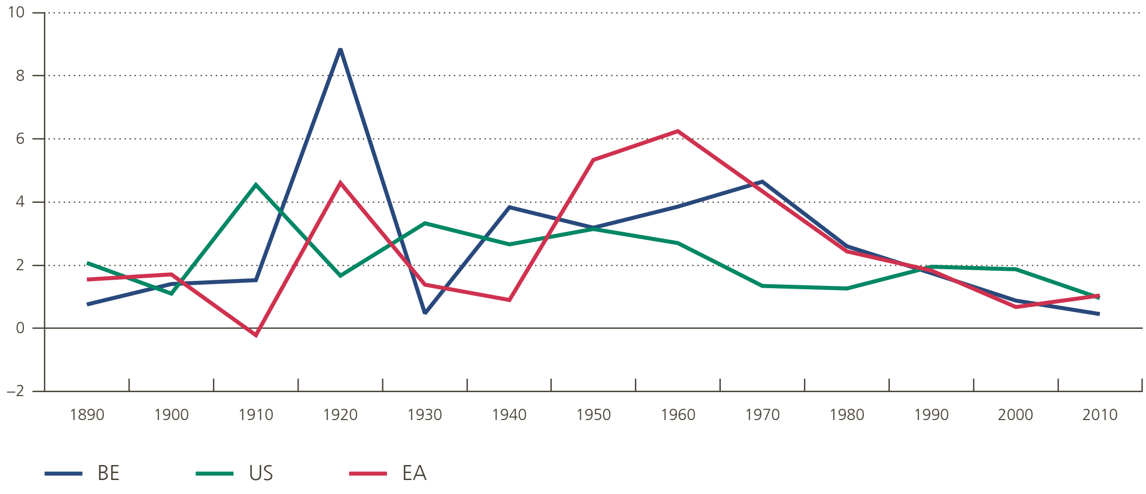
In sum, AI is deeply transforming processes in a wide range of activities and thus has the potential to start a new wave of high productivity growth. As the National Productivity Board noted in its last annual report, "productivity growth is the most important driver of long-term income growth, which in turn determines not only the evolution of living standards but also the scope for government to pursue policy". The hopes raised by the AI revolution are therefore incredibly high.

However, despite the increasing adoption of AI and other technological advancements, productivity growth in many developed economies has been relatively slow in recent years (see Figure 4). This deceleration is widespread, having occurred across the OECD and, more recently, in many large emerging economies (Sylverson, 2017).

Figure 4

Productivity growth in Belgium, the European Union and the United States

(in %)



Source: Bergeaud *et al.* (2016).

We seem to be confronted once again with Solow’s paradox (1987), namely “you can see the computer age everywhere but in the productivity statistics”. The same is true with AI: it can be seen everywhere, but there is not yet an observable improvement in productivity growth.

This raises the question of whether AI is having the expected impact on productivity, or if there are other factors at play. Brynjolfsson *et al.* (2018b) argue that lags in the implementation of AI have been the biggest contributor to the paradox. Indeed, the use of AI is not yet widespread. As demonstrated in Section 1, only 8 % of firms in the EU were using AI in 2021. In addition, they claim that without complementary innovations, the full potential effect of AI on productivity growth will not be felt. It will take time for companies to adopt and integrate these new technologies into their operations and for workers to develop the skills necessary to use them. They therefore believe that it is still too early for information and communication technologies in general to have had much impact. This is not specific to AI. Electricity was introduced at the end of the 19th century, but it’s impact on productivity only materialised after WWII.

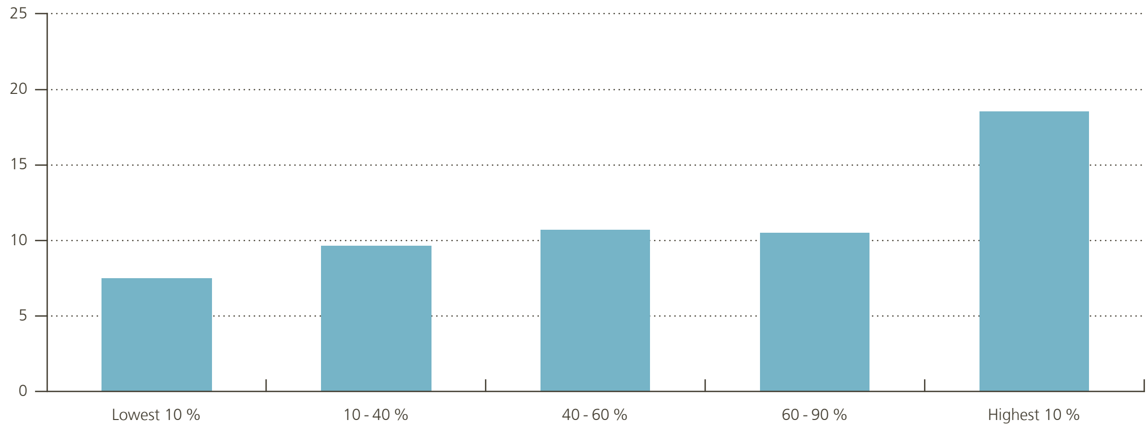
A second argument often mentioned in the literature is that of measurement error. GDP, which is a common measure of economic growth, may not accurately capture the value created by digital goods and services. Much of the most valuable online content is free and therefore is not captured by an increase in the consumer surplus when calculating GDP and productivity growth (Scott and Varian, 2015; Brynjolfsson *et al.* 2017; Greenstein and McDevitt, 2011; Goolsbee and Klenow, 2006). To illustrate this point, Brynjolfsson *et al.* (2017) asked people how much they would agree to be paid to not have access to Facebook for one month. They estimated a value of $ 750 per person per year, which corresponded to $ 18 billion for the United States. Earlier, Varian (2009) also calculated the savings of time generated by the Internet (e.g. searching for information) and estimated that Google saves $ 22 per person per year.

Also, it is important to consider the role of other factors such as macroeconomic policies, product market regulations, labour market regulations, and the broader social and economic context. These may also play a role in shaping productivity growth and the impact of AI. Overall, there is no single answer to the productivity puzzle, and it is likely that a combination of factors is at play.

Figure 5

Firms using at least one AI technology [1], sorted by level of productivity [2] in Belgium

(in %)



Source: Federal Planning Bureau.

1 AI technologies include text mining, speech recognition, natural language generation, image recognition and processing, machine learning, AI based software robotic process automation, autonomous robots, self-driving vehicles and autonomous drones.

2 Labour productivity measured by turnover per employee.

While country-level statistics do not reveal significant productivity growth, firm-level analyses present a different story. Researchers such as Gal *et al.* (2019), for example, have demonstrated that more productive firms are on average more digitalised and vice versa. A recent analysis by the Federal Planning Bureau on the use of AI by companies in Belgium revealed similar results: AI is most widespread amongst the 10% most productive companies (at 18.5%) and least widespread amongst the 10% least productive firms (at 7.5%). Of course, those figures do not necessarily imply that AI impacts firm productivity. The most productive firms could simply be those with the greatest financial capacity to invest in AI. Still, the FPB report shows that the relationship between the use of AI and firm productivity remains positive even after controlling for firm size and age, industry and complementary ICT applications such as broadband and cloud computing.

A large and growing body of literature confirms a direct link between the adoption of digital technologies and firm-level productivity. It should be noted, however, that this literature has focused to date on ICT and automation rather than specifically on AI. That being said, various factors can enhance or mitigate this relationship, including organisational change, skills, firm size and age, regulation, spillovers and the existence of a network (see e.g. others Brynjolfsson and Saunders, 2010; Draca *et al.*, 2009; Bloom *et al.*, 2012). A recent paper by Kanazawa *et al.* (2022) also confirmed the link between the use of AI and worker productivity. To do so, they estimated and compared the cruising time of taxi drivers, that is the time needed to find a new customer, when using AI and without the use of AI. Interestingly, they found that driver productivity improved only for low-skilled drivers, reducing the productivity gap between high- and low-skilled drivers by 14%. Similar results have been found by Brynjolfsson *et al.* (2023), who studied the use of a generative AI-based conversational assistant on the productivity of customer support agents. They found a 14% increase in worker productivity with a large impact on new and low-skilled workers and little effect on experienced and highly skilled workers.

3. The effects of AI on competition between firms

AI has the potential to significantly modify competition between firms by changing the way businesses operate and compete with each other. AI can help firms automate routine tasks, reduce errors and optimise processes, resulting in improved efficiency and cost savings and giving them a competitive advantage over those that do not use AI. It can also help firms understand customer preferences and behaviour, enabling them to offer personalised goods and services. This can enhance the customer experience and create brand loyalty. In addition, AI can analyse vast quantities of data and help firms make better decisions, notably with regard to the optimal price of goods and services.

Indeed, as mentioned above, one of the most powerful forms of AI for the firms studied by researchers is machine learning. This type of algorithm is increasingly used to set prices, mainly online. For example, online retailers can now not only change their prices more frequently, but they can also automate responses to price changes by competitors (Brown and MacKay, 2023). Researchers recently started to analyse this new phenomenon through experiments and models simulating online competition between firms using pricing algorithms. The results are still ambiguous, however. Some studies show that firms converge to collusive outcomes, implying higher prices and profits as well as the punishment of competitor deviation, without any communication between the algorithms used by firms (Klein, 2021; Calvano *et al.*, 2020). The algorithms simply "learn" after some iterations that a collusive outcome is optimum and how to react if other firms deviate from it. Other papers reveal more nuanced results, showing that while collusion is indeed possible in some markets where it was previously unsustainable, in other markets, improved transparency may render collusion no longer possible (Miklos-Thal and Tucker, 2019; O'Connor and Wilson, 2021).

Using a unique dataset on Germany's retail gasoline market, Assad *et al.* (2020) empirically measured how competition between firms is affected by the adoption of AI. By mid-2017, algorithmic-pricing software had become widely available in the sector. The dataset allowed the authors to track prices at high frequency and to identify gas stations that adopted the software (instrumented by headquarter-level adoption decisions). Their analysis revealed that firms' margins increased by 9 % with adoption of the software, but only in non-monopoly markets. In the event of a duopoly, margins rose by 28 % if both firms adopted the AI software but did not change if only one firm did so. While these results cannot yet be extended to other markets, they are a first illustration with real data that algorithmic pricing could facilitate tacit collusion.

Algorithms are changing not only relationships between firms but also potentially between firms and consumers. Indeed, technological advancements allow firms to learn more about consumer preferences and as a result price their products more accurately. Researchers have noted that big data may enable first-degree price discrimination, which was previously thought to be difficult to carry out in many markets (Ezrachi and Stucke, 2016). Furthermore, accurately determining optimal personalised pricing may lead to an increase in firm revenue (Shiller and Waldfogel, 2011; Shiller, 2014). Nevertheless, Kehoe *et al.* (2022) found that both firm profits and consumer surplus may increase or decrease depending on how certain consumers are about their product preferences. In addition, they highlight that, thanks to AI, total welfare is higher in all cases under discriminatory pricing than when uniform pricing is applied.

Algorithms are also an important tool used by platforms to recommend products to consumers. They help them discover new products, which can increase consumer welfare, and help small firms sell their products more easily. Conversely, if algorithms encourage people to buy "superstar" products, the popularity of these products will be reinforced, as will the position of the firms selling them. Fleder and Hosanagar (2009), however, show that even with a decrease in aggregate diversity of product sales, consumers can be better off because, at the individual level, diversity is still increasing. Recommender systems push consumers towards new products, even though these are often the same products at the aggregate level. Still, based on a study of Spotify, Anderson *et al.* (2020) demonstrated that algorithmic recommendations are more effective for users with a lower preference for diversity.

Wan *et al.* (2023) quantified the economic benefits of recommender systems for consumers compared to firms. Their study found that product recommendations significantly help consumers discover lower-priced items on a website, resulting in a higher likelihood of making a purchase (and thus a reduction in failed search efforts) and an overall lower price for the purchased products. Specifically, an extra page view of recommended products increased the probability of making a purchase by 15 % and resulted in a $ 1.59 decrease in the purchase price. The implementation of product recommendations produced a surplus of $ 56,631, equating to 3.8 % of total sales. Two-thirds of this amount went to the retailer as additional revenue, while consumers retained the remaining one-third as price savings.

Finally, AI and more generally digital technologies[1] can result in lower costs in the economy (Goldfarb and Tucker, 2019). The first type of cost which can be lowered by digital technologies is search costs, as it is easier for consumers to compare prices. This can potentially lead to a decrease in prices and price dispersion. However, search costs are endogenous, and firms can manipulate the search process to maintain higher margins and prices (Brynjolfsson *et al.*, 2003). Low search costs can also affect the organisation of a firm, potentially increasing or decreasing centralisation (Garicano, 2000; Bloom *et al.*, 2014). The second type of cost is replication costs, which can be lower for digital goods, meaning it is possible to bundle thousands of digital products together (Lerner and Tirole, 2002). Open-source software is an example of this (e.g. Netflix, Disney+, Spotify, Apple Music, etc.). It should be noted, however, that while public benefits can be created, so can public "harms", such as spam or online crime (Rao and Reiley, 2012; Moore *et al.*, 2009). The third cost is transportation costs,

1 Artificial intelligence (AI) and digital technology are related concepts but refer to different things. Digital technology means any technology that entails the use of digital signals and processing. This can include computers, smartphones, the Internet and various other electronic devices. Digital technology can be used for a wide range of applications, from communication and entertainment to business and scientific research. AI, on the other hand, refers specifically to the ability of machines to perform tasks that would normally require human intelligence. While AI relies heavily on digital technology (such as computers and data storage), it is distinct in its ability to learn, reason and make decisions based on complex data. In other words, digital technology is a broad term that encompasses many different types of technology, while AI is a more specific subset of digital technology which involves the use of machine intelligence to perform tasks.

which approach zero for digital goods, allowing isolated individuals and companies to connect to the global economy and rural consumers to access the same digital products and services as others. However, distance still matters due to available offline options, spatially correlated tastes and the presence of social networks. The fourth type of cost which can be lowered is tracking costs, thereby enabling personalised markets and the ability to price discriminate based on an individual's past behaviour (Fudenberg and Villas-Boas, 2007, 2012). To date, low online tracking costs have not really been used to charge different customers different prices but instead to show different customers more appropriate, relevant and profitable advertising. The fifth cost is verification costs, which can be lowered through online rating systems, enabling the creation of trust in the absence of repeated interaction (Ba and Pavlou, 2002). For better-rated firms, this leads to higher prices and revenue (Melnik and Alm, 2002; Livingston, 2005; Houser and Wooders, 2005; Lucking-Reiley *et al.*, 2007). Lower verification costs also help individuals make more secure, easier payments.

4. The consequences of AI on the labour market

The rise of digital and automation technologies has generated much debate regarding their impact on the labour market and employment. On the one hand, if these technologies replace human capabilities and become a substitute for labour (Trajtenberg, 2018), certain types of jobs could be eliminated. On the other hand, if they are complementary to labour, as argued by Acemoglu, digital technologies could magnify or enhance human capabilities and displace workers from routine and repetitive tasks. In a recent paper, co-written with Restrepo [1], Acemoglu posits that a job can be decomposed into tasks and that the impact of AI on a given job will depend on which specific tasks are performed by AI. In addition to the displacement effect, new tasks will be created for which humans will have a comparative advantage over machines.

The decomposition of jobs into tasks has also been studied by Frey and Osborne (2017), who identified which types of tasks are at risk of computerisation and which are not (basically skills and abilities related to perception, manipulation, creativity and social intelligence). Then, based on the O*NET database, they defined which occupations are at higher risk of automation with reference to the number of tasks within each occupation. They found that 47 % of total employment in the US is at risk of computerisation. Other researchers, using the same methodology, have calculated this rate for other countries (see e.g. Nedelkoska and Quintini, 2018; Arntz *et al.*, 2017). In 2016, the High Council for Employment estimated that 39 % of employment in Belgium was at risk of computerisation.

The literature has also highlighted a form of job polarisation due to automation and digital technologies, with the largest share of automatable jobs being medium-skilled. This is also true for Belgium although less pronounced than in other countries (De Sloover and Saks, 2018).

Based on the same type of reasoning, a growing body of literature is attempting to assess the effects of the use of AI on employment. Brynjolfsson *et al.* (2018a) state that AI has the potential to drastically reshape the employment landscape since it will affect not only low- and medium-skilled jobs but also a number of high-skilled occupations. Lassébie and Quintini (2023) presented the degree of automatability of approximately 100 skills and abilities, applied to occupations, to assess the number of jobs potentially affected and the workers most at risk. They found that thanks to advances in AI and robotics, certain high-level cognitive skills can now be automated. However, high-skilled occupations continue to be less at risk as they require skills and abilities that remain important bottlenecks to automation (i.e. negotiation, social perceptiveness, assistance to and caring for others, technology design, persuasion, complex-problem solving and active listening). The study showed moreover that the jobs at highest risk of automation will not disappear completely, as only 18 % to 27 % of skills

1 Acemoglu and Restrepo (2019)

and abilities required in these occupations are highly automatable. Most occupations are indeed characterised by both bottlenecks and highly automatable skills and abilities.

The type of AI will also determine its effects on employment. Holm and Lorenz (2021) analysed the use of AI by employees in Denmark and found that the effects of AI vary depending on whether it provides orders to humans or information for further human handling. Agrawal *et al.* (2019) further developed this idea and focused on machine learning, arguing that recent AI achievements are mainly due to advancements in this field. While machine-learning algorithms can replace human labour in prediction tasks, predictions remain important inputs for human decision-making, meaning improvements in prediction can increase the returns on human labour in decision-making processes. However, several technical challenges need to be addressed in order for AI to be able to complement human labour, including effective human-AI collaboration and an optimal distribution of tasks between workers and machines. Despite a growing body of literature on this topic, human-AI teams often do not outperform AI-only or human-only teams (Littman *et al.*, 2021). Furthermore, it may not always be clear how to divide up tasks, as some occupations rely on a bundle of tasks which cannot be performed independently.

Milanez (2023), based on 100 case studies in eight OECD countries, confirmed the existence of job reorganisation towards tasks for which humans have a comparative advantage. The case studies indicated that AI is impacting a wide range of tasks and workers, including those performing non-routine tasks, for example relieving technicians of the non-routine task of trouble-shooting equipment failures by anticipating breakdowns before they occur. The workers most affected by AI are in a range of occupations, suggesting that AI has the potential to impact workers of all skill levels, across a wide variety of firms and sectors. Unlike past technologies such as IT and robotics, which replaced routine and manual tasks done by mainly low-skilled workers, the distributional consequences of AI could be fundamentally different since it could replace non-routine cognitive tasks of high-skilled workers (Webb, 2020). To date, the case studies suggest that employment levels have remained steady in the face of AI adoption, although there is some evidence of slowed job growth. The case studies provide limited evidence of redundancies linked to AI. Instead, firms appear to have reallocated workers to other business areas or to have made adjustments via slowed hiring and attrition. This finding was also made by Acemoglu *et al.* (2022), who showed that some firms with greater exposure to AI tended to have lower hiring, although the result was not robust across all specifications. The relationship between AI adoption and the level of employment is therefore still unclear in the literature, which could be due in part to the immaturity of AI technologies (Fleck *et al.*, 2022), as well as to the fact that AI can lead to both job creation[1] and job destruction (Hunt *et al.*, 2022).

The development of AI will create new tasks and jobs through its own need for further development, maintenance and operation (Wilson *et al.*, 2017). Demand for AI specialists and AI skills will increase significantly in the future. In Belgium, 15.4 % of firms with 10 employees or more recruited or tried to recruit ICT specialists in 2022, according to Eurostat data. This share was 11.1 % in 2012.

Moreover, the impact of AI on employment growth is also related to the digital skills of workers. Georgieff and Hyee (2021), for example, found that in occupations with high computer usage and thus better digital skills, exposure to AI leads to higher employment growth. Implicitly, this result points to a greater ability on the part of workers to adapt to AI technologies and therefore to reap the benefits they offer. Put differently, it is possible for AI technologies to complement humans, enabling them to perform tasks differently and potentially more efficiently than before (Felten *et al.*, 2019). Occupations susceptible to major change thanks to AI include business professionals, legal, social and cultural professionals, managers, and science and engineering professionals. The various AI applications available for these occupations include the identification of investment opportunities, optimisation of production in manufacturing plants, identification of problems on assembly lines, analysis and filtering of job interviews, and translation.

1 The development of AI will create new tasks through its own need for further development, maintenance, and operation (Wilson *et al.*, 2017). Demand for AI specialists and AI skills will increase significantly in the future. In Belgium, 15.4 % of firms, with 10 employees or more, recruited or tried to recruit ICT specialists in 2022, according to Eurostat data. This share was 11.1 % in 2012.

The ability of firms and workers to adapt to the implementation of AI via job reorganisation therefore depends on existing skill levels and the training efforts made by firms to upskill workers when necessary. Nevertheless, in 2021, 18.6 % of the population in Belgium had a low level of digital skills, which is higher than the EU average (17 %). This finding is reflected most sharply in the unemployed segment of the population (of which 22.1 % have low digital skills in Belgium compared to 17.8 % in the EU) rather than among workers (17.9 % versus 17.7 %, respectively). While the percentage of individuals with low digital skills is smaller amongst the highly educated (14 %), it is interesting to note that this percentage is highest for those with a medium level of education (22 %) rather than a low level (19.2 %) and that this statement was verified in 19 of the 27 EU Member States.

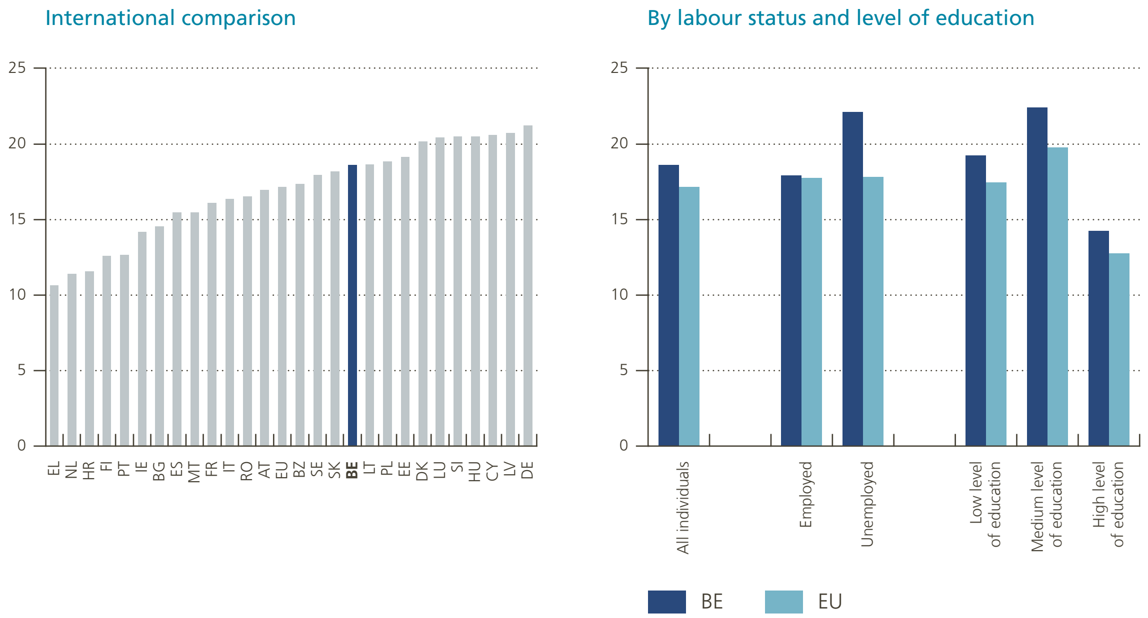
Lane *et al.* (2023) revealed that employers are addressing skill shortages brought about by the adoption of AI primarily through employee training. Almost 70 % of surveyed employers indicated that they had retrained or upskilled internal talent and more than half of surveyed workers confirmed that their company provided training to learn how to better work with AI.

Other literature shows that the need for AI skills remains limited. Bessen *et al.* (2018) conducted a survey of AI start-up leaders and found that most AI applications do not require specialised training or STEM skills. Only a small percentage of firms surveyed indicated a need for expert coding or data skills, with the majority requiring only general computer knowledge or no special skills at all. However, it is important to note that, when needed, these skills are particularly difficult to find and usually highly geographically concentrated. For example, LinkedIn Economic Graph (2019) revealed that the UK, France and Germany already account for half the AI workforce in Europe. Even within countries, Flagg and Olander (2020) found that AI skills are concentrated in localised hubs. Along with a (limited) increase in demand for AI skills, employers report rising demand for highly educated workers in general and also for "human" skills such as interpersonal skills and empathy. The gradual nature of the shift in skill requirements seems to be due to the time it takes for work roles and occupational structures to change (Handel, 2020).

Figure 6

Individuals with low digital skills

(in %, individuals aged 15 or more)



Source: Eurostat.

In addition to its impact on the level of employment, AI is expected to influence job quality, meaning the quality of the working environment, earnings and job security (Cazes *et al.*, 2015). A study of Japanese workers found that the reorganisation of tasks following AI adoption increased stress, despite contributing to greater job satisfaction (Yamamoto, 2019). Based on case studies in the manufacturing and banking sectors in several European countries, Jaehrling (2018) found that digital technologies tended to increase workloads, intensify work-related stress and lead to job destruction. Furthermore, there is concern about AI technologies being used to monitor workers, which contributes to increased stress and mistrust (Trade Union Congress Labour Force Survey in the UK, 2021). Lane *et al.* (2023) also found that workers are concerned about the impact of AI on job stability.

The impact of AI technologies on wages has been more widely studied, with evidence suggesting that AI has had a positive impact on wage growth but only for certain types of workers (Lane and Saint-Martin, 2021). Using US data, Felten *et al.* (2019) found that the effect was driven by high-income occupations, with no link between exposure to AI and wage growth for low- or middle-income occupations. Fossen and Sorgner (2022) found that more exposed occupations were linked to wage growth overall, with stronger effects for individuals with higher educational attainment and more experience.

Overall, the impact of AI on job quality is not fully understood, and the existing evidence suggests a potential for negative impacts, particularly in terms of increased stress, job security and worker monitoring. While the evidence on the impact of AI on wages is more promising, the benefits seem to be concentrated in high-income occupations and individuals with higher educational attainment and more experience.

Finally, the functioning of the labour market itself could be affected by AI since it can be used as a new tool to match workers and employers. AI-powered recruitment tools can help organisations streamline the recruitment process by automating tasks such as resume screening, candidate sourcing and interview scheduling. The use of AI by public employment services to enhance jobseeker profiling or job matching is becoming more widespread (OECD, 2022). However, it is important to note that AI should be used as a tool to support recruitment decisions, not to replace human judgment.[1] Human recruiters should still be involved in the recruitment process to ensure that hiring decisions are fair, unbiased and based on a holistic view of the candidate's skills, experience and qualifications. Indeed, the use of AI in the hiring process has the potential to decrease or increase the risk of discrimination, depending on how it is implemented and used. On the one hand, AI algorithms can be programmed to evaluate candidates based on objective criteria such as skills, experience and qualifications, rather than factors such as race, gender or age. This could help reduce the influence of unconscious bias in the hiring process and increase the diversity of the candidate pool. On the other hand, AI algorithms can also perpetuate bias and discrimination if they are trained on biased data or programmed to prioritise certain characteristics or criteria associated with certain groups. For example, if an AI algorithm is trained on data that is biased against certain minority groups, it may be more likely to reject candidates from those groups, even if they are highly qualified.

5. Other risks related to the use of AI

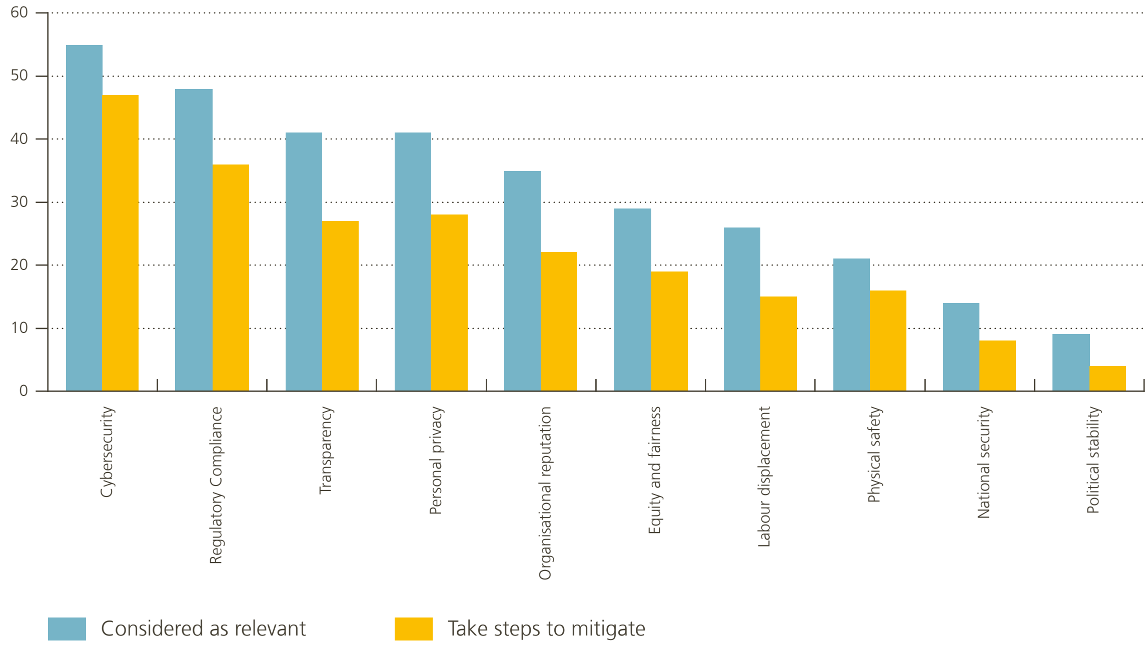
According to McKinsey (2021), cybersecurity is the most-often cited risk associated with the adoption of AI, followed by regulatory compliance, transparency, and privacy. Other risks include organisational reputation, equity and fairness, labour displacement, physical safety, national security, and political stability. As shown in Figure 7, while organisations recognise the risks related to AI, only a small share are taking concrete steps to mitigate those risks, which calls for a policy response.

1 See the High Council for Employment (2021)

Figure 7

Firms' perception of the risks associated with the adoption of AI

(in % of respondents, 2021)



Source : Standford Institute for Human-Centered Artificial Intelligence, based on McKinsey (2021).

Regarding security issues, various risks need to be taken into account. First, AI systems are vulnerable to cyber-attacks just like any other computer system. However, AI systems can be particularly attractive targets for hackers, as they often contain large amounts of sensitive data and are used to take critical decisions. If an AI system is compromised, it can lead to data breaches, privacy violations or even physical harm. Secondly, there is a risk that AI systems could be designed and used for malicious purposes. For example, AI systems could be programmed to spread misinformation, engage in cyber-attacks, or carry out physical attacks. AI technology can also be used to create convincing fake videos, images or audio recordings, known as deepfakes. These deepfakes can be used to spread misinformation or manipulate public opinion. For example, a deepfake video of a political figure could be used to spread false information and influence an election.

Moreover, as AI systems become more advanced, they may take decisions autonomously. This raises questions about who is responsible for these decisions and whether they can be held accountable for any harm caused. For example, if a self-driving vehicle causes an accident, the question arises as to which party is reponsible and can be held liable – the manufacturer, the software developer or the owner of the vehicle. In addition, in fields such as healthcare, the use of machine-learning-based diagnosis and robotic surgery could shift liability from healthcare providers to device manufacturers. These questions of liability and accountability are complex and require careful consideration. In the absence of clear rules to determine liability for defective AI products involving numerous parties, companies may be hesitant to invest in the technology. The diffusion of AI in the economy could therefore be compromised (Galasso and Luo, 2018). In response to these potential risks, the European Parliament adopted a resolution in February 2017 to regulate the use of artificial intelligence (European Parliament, 2017).

Data is a fundamental component of artificial intelligence, and machine learning uses data to make predictions about individuals' desires and behaviour. However, this reliance on data also raises privacy concerns. This is especially true if the data collected are sensitive or personal. These data can be used for purposes the data subjects did not intend or of which they may not be aware. For example, AI systems can be used to track individuals' movements or preferences, potentially violating their privacy. According to Tucker (2018), privacy is challenging for three reasons: (1) data can be retained longer than intended due to cheap storage, (2) data can be repurposed for uses other than the originally intended one due to nonrivalry and (3) data created by one person can contain information about others due to externalities. The regulation of privacy has a significant impact on innovation in data-driven industries, as highlighted by Goldfarb and Tucker (2019). If privacy protection is insufficient, consumers may be hesitant to engage in market transactions where their data are vulnerable. Conversely, excessive privacy regulation can prevent firms from using data to innovate. In addition, differences in privacy policies between countries could influence the development of AI. If a relatively lax privacy policy deemed optimal for AI diffusion, countries with such policies could initially benefit. However, there is a risk of a "race to the bottom" in this area, meaning countries could lower their privacy standards to get ahead of one another in terms of AI. Trade agreements could prevent such a scenario by specifying international privacy standards. The extent to which AI-related rents will be localised is still uncertain, given that the industrial applications of AI are still in their infancy. Nevertheless, governments worldwide are investing in AI, making a race to the bottom when it comes to privacy a potential point for attention in future trade agreements (Agrawal *et al.*, 2019).

AI systems can be opaque, meaning it can be difficult to understand how they take decisions or why they make certain recommendations. This lack of transparency can make it difficult to determine whether the systems are taking ethical decisions. For example, a credit rating system may make decisions about whether to extend credit to individuals based on a complex algorithm, but it may be difficult for individuals to understand how the algorithm arrived at its decision. This lack of transparency can erode trust in AI systems and make it harder to ensure that they are being used ethically.

A well-known example of potential bias in AI is the technology developed by computer scientists at Amazon to screen resumes. Their technology used algorithms to analyse ten years of previous job-candidate data and then rated new candidates from one to five stars. The new system, likened to an online shopping review, was initially praised by insiders as a "holy grail" for the company's recruitment efforts. However, as the algorithm was tested, executives discovered that it was generating negative coefficients for terms associated with women, thereby amplifying male dominance in the tech industry. Amazon's experience highlights the challenge of ensuring algorithmic fairness as more aspects of daily life are digitised, with ethical and distributional implications becoming increasingly important.

Various explanations for biased algorithmic outcomes have been proposed in the literature. Cowgill and Tucker (2020) summarise four of them: (1) unrepresentative training samples, i.e. the fact that training data do not include the performance outcomes of those who were not chosen (e.g. candidates who were not hired or loan applicants who were rejected); (2) the mislabelling of outcomes in training samples, i.e. the group usually facing discrimination could be labelled as low performing in the training data; (3) biased programmers, i.e. software engineers may be more likely to belong to a specific group of the population and can transmit their own biases to their programs; and (4) algorithmic feedback loops, i.e. a program may include its own prediction in the training data so that it affects the outcome it is supposed to predict and therefore amplifies the bias.

A recent analysis by Lambrecht and Tucker (2019) attempted to better understand how an algorithm designed to be gender neutral could yield gender-biased results. To do so, they studied online advertisements for science, technology, engineering and mathematics (STEM) education based on an algorithm that was supposed to simply optimise cost-effectiveness. This same test has been carried out in 191 different countries across the world, with the same result: the algorithm tends to show the ad more often to men than women. Contrary to what might be expected, the authors show that this bias cannot be explained by discriminatory behaviour on the part of consumers (e.g. women were less likely to click on the ad) or bias in the data the algorithm was trained on (e.g. a different level of discrimination against women in different countries). Instead, the result was due to a purely economic factor (cost savings): on average, it costs advertisers more to show ads to female viewers than male viewers because women are more likely to control household purchases and are thus seen as more "valuable" targets for advertisers. The authors provide evidence that women are more likely to make purchases after clicking on an ad than men, which may explain why advertisers are willing to pay more to show ads to women and therefore why the algorithm, in order to reduce the cost, is more likely to decide to show the ad to men.

6. Conclusion and policy implications

AI has the potential to revolutionise various industries, from manufacturing to the services sector, and to raise productivity growth by automating tasks, analysing big data and freeing up employees for more complex work. However, productivity growth in many developed countries has lagged in recent years, raising the question of whether AI has had the expected impact or if other factors are at play. Delays in AI implementation, measurement errors, the role of complementary innovations, macroeconomic policies, and the social and economic context are all factors that could affect productivity growth. That being said, while statistics at country level do not show significant growth in productivity, research indicates that more productive firms tend to be more digitalised and confirms a positive correlation between firm digitalisation and productivity growth.

The impact of digital and automation technologies on the labour market and employment is a subject of debate. While some believe that these technologies can replace human capabilities and will ultimately result in fewer jobs, others argue that they can enhance human abilities and eliminate routine and repetitive tasks. Jobs can be broken down into tasks, and the impact on employment depends on which specific tasks are performed by AI. New tasks will also be created, for which humans have an advantage over machines. Some occupations are at greater risk of automation, particularly medium-skilled jobs, although even jobs at the highest risk of automation are not expected to disappear completely.

The distributional consequences of AI could be fundamentally different from those of past technologies such as IT and robotics, which mainly replaced routine, manual tasks associated with low-skilled jobs. Instead, AI could replace non-routine cognitive tasks performed by more highly skilled workers. However, to date, research suggests that employment levels have remained steady despite AI adoption, although there is evidence of slowed job growth. Rather than redundancies linked to AI, firms have reallocated workers to other business areas or made adjustments via slowed hiring and attrition.

AI has the ability to outperform humans in certain tasks. It can learn and improve quickly from large data sets, whereas humans may require much more time to develop their skills. Additionally, machine translation systems using AI can translate texts more quickly and at times more accurately than humans. AI can be highly precise for the performance of certain tasks such as image recognition, fraud detection and outcome prediction. It can also make more informed and accurate data-driven decisions than humans, who can be influenced by bias and emotion. Nonetheless, there are certain areas in which humans have an advantage over artificial intelligence. For instance, humans possess a better understanding of emotions, intentions, and communication nuances than AI. Moreover, while AI can generate ideas and creations, it cannot replicate the originality and creative thought processes of humans. Humans can also grasp the context of a situation and make decisions accordingly, whereas AI relies on data and instructions. Humans possess the ability to solve complex problems using intuition and experience, while AI needs precise instructions and massive data. It is important to acknowledge that humans and AI have distinct strengths and weaknesses but that humans can use AI to obtain optimal results. In uncertain and unpredictable circumstances, humans have an advantage when it comes to making decisions since they can rely on intuition and experience, which are more challenging for AI.

As AI continues to advance and becomes more prevalent in our economies and societies, policymakers will need to respond to ensure that the benefits of AI are maximised while minimising the potential risks and negative impacts. Policymakers can develop a comprehensive strategy for AI that takes into account its potential economic, social and ethical impacts. Such a strategy could outline priorities for AI research and development, investment in infrastructure and talent, and a regulatory framework. Support for innovation in AI could also be made a policy priority, by providing funding for research and development, promoting collaboration between industry and academia, and providing incentives for companies to invest in AI. To avoid skill shortages, policymakers could foster the development of AI talent by investing in education and training programmes that teach the skills needed to work with AI, such as data analysis, programming and machine learning. The ethical and regulatory challenges associated with AI could also be addressed by developing a framework for the responsible development and deployment of AI, such as guidelines on data privacy, transparency and accountability. Finally, policymakers could facilitate international cooperation on AI by working with other countries to develop common standards and guidelines for the development and deployment of AI.

The European Union is in the process of preparing a significant regulation on artificial intelligence, but the rapid development of advanced tools such as conversional software (e.g. ChatGPT) is causing complications. Despite years of work, the EU only recently presented a draft regulation on AI, which aims to make Europe a leader in innovation while ensuring safety and protecting user rights. The complexity of the legislation could delay its adoption until next year. The regulation will apply to anyone providing a product or service using artificial intelligence and will cover a wide range of systems, including those used by businesses, the public sector and law enforcement. The proposed legislation will classify AI tools based on perceived risk, with different obligations imposed on governments and companies depending on the level of risk. In addition, high-risk AI tools will be made subject to rigorous risk assessments and it will be required to keep detailed records of their activities. High-risk categories include areas such as law enforcement, migration, critical infrastructure, education and the administration of justice. At the highest level (“unacceptable”), AI-based tools will be banned altogether. The proposed AI Act will apply in conjunction with existing legislation, such as the General Data Protection Regulation (GDPR), to ensure that the use of AI is strictly controlled and regulated.

In sum, the development of artificial intelligence brings with it benefits, challenges and risks in equal measure. AI could well be the next general-purpose technology, driving productivity growth across the economy, but its potential impact on the economy and jobs must be scrutinised and its development wisely regulated.

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Conventional signs

e.g.	*exempli gratia* (for example)
i.e.	*id est* (that is)

List of abbreviations

Countries or regions

BE	Belgium
DE	Germany
EE	Estonia
EL	Greece
ES	Spain
IE	Ireland
FR	France
IT	Italy
CY	Cyprus
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	The Netherlands
AT	Austria
PT	Portugal
SI	Slovenia
SK	Slovakia
FI	Finland
BG	Bulgaria
CZ	Czech Republic
DK	Denmark
HR	Croatia
HU	Hungary
PL	Poland
RO	Romania
SE	Sweden
EU	European Union
UK	United Kingdom
US	United States

Abbreviations

AI	Artificial intelligence
AR	Augmented reality
FPB	Federal Planning Bureau
GDP	Gross domestic product
GDPR	General Data Protection Regulation
GPT	General purpose technology
ICT	Information and communication technology
NBB	National Bank of Belgium
OECD	Organisation for Economic Cooperation and Development
Statbel	Belgian statistical office
STEM	Science, technology, engineering and mathematics
VR	Virtual reality

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