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What is holding back artificial intelligence adoption in Europe?

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Executive summary

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ARTIFICIAL INTELLIGENCE (AI) is considered a key driver of future economic development, expected to increase labour productivity and economic growth worldwide. To realise these gains, AI technologies need to be adopted by companies and integrated into their operations. However, it is unclear what the current level of AI adoption by European firms actually is. Estimates vary widely because of uneven data collection and lack of a standard definition and taxonomy of AI.

WHAT IS CLEAR is that AI adoption in Europe is low and likely running behind other parts of the world. Discussions on the barriers to AI advancement often mix up different stages of innovation – research, development and adoption. Each stage is constrained by the availability of skills, data and financing in the European market, but there are nuances in how these barriers arise in each of the three stages.

THIS POLICY CONTRIBUTION focuses on the final stage, AI adoption. We discuss theoretical and empirical evidence of the drivers of AI adoption. We outline the relevant barriers to adoption for European firms in terms of human capital, data availability and funding, and make international comparisons where possible.

TO ACCELERATE THE roll-out of AI technology across the European Union, policymakers should alleviate constraints to adoption faced by firms, both in the environmental context – labour market, financial market and regulation – and in the technological context – data availability, basic digitisation of businesses and technological uncertainty.

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1 Introduction

Artificial intelligence (AI) is considered a key driver of future economic development. Firms that have filed AI patents have been shown to experience labour productivity increases of three to four percent[1]. Widespread adoption of AI could therefore boost growth in European economic activity by almost 20 percent by 2030 (Bughin *et al*, 2019). To realise these gains at macroeconomic level, AI technologies need to be adopted and integrated at firm level.

However, AI adoption in Europe is running behind other parts of the world. To accelerate the take-up of AI in European firms, policymakers need to understand the barriers that hold firms back from adopting AI. Insights into firms' technology adoption decisions are needed to steer policy and to ensure that AI technologies benefit workers – by making the technology trustworthy, easy to use and valuable in day-to-day work (Hoffmann and Nurski, 2021).

2 Measuring AI advancement in Europe

Understanding the goals and status of AI advancement in Europe requires an understanding of each of the steps in the AI production chain: AI research, AI development and AI adoption. AI research refers to the discovery of new techniques for making intelligent decisions based on data, and is usually done by universities or private research laboratories. AI development refers to application of those new techniques to develop AI products or services that address business needs; this is usually done by technology companies (either big tech or AI start-ups and scale-ups). Finally, AI adoption refers to the use of AI products or services in companies' internal production processes or service delivery (Table 1).

Promoting AI development matters for Europe's strategic autonomy because the development of AI technologies in Europe means less dependence on foreign technologies. It also helps to ensure that AI technologies align with European values. However, when it comes to increasing the productivity of European firms and ensuring their international competitiveness, promoting AI adoption is much more relevant. AI development can be tracked by the number of European AI patents or unicorns[2], while AI adoption requires indicators of the acquisition of AI products (or investment) by regular non-AI European businesses.

Such a detailed understanding helps in analysing the constraints or barriers facing AI research, development and adoption. For example, the lack of public funding and venture capital are often cited as financial barriers to AI advancement in Europe (Tricot, 2021). However, these financial resources are mostly relevant for AI research and AI development. The financial constraints on AI adoption by regular (non-tech) firms can be better addressed using other instruments, such as tax deductions or AI technology investment subsidies.

A similar analysis can be done for the lack of access to external (private and public) datasets in Europe, another often-cited barrier to AI advancement (Castro *et al*, 2019; Linck, 2021). While large datasets from external sources are crucial for testing new techniques (AI research) and for training new models in AI products (AI development), they are less crucial for AI adoption by regular businesses. For non-AI firms that want to buy AI products or services, the availability of their own internal data sources is much more crucial. For example, a French language AI chatbot might be trained on a large repository of French language texts during development. However, when a French retailer buys this chatbot for integration into its customer services, the bot needs fine tuning using that business' own customer interaction data

1 Based on studies of firms in the United States and firms worldwide. See Alderucci *et al* (2020) and Damioli *et al* (2021).

2 A 'unicorn' refers to a privately held startup company valued at over $1 billion.

(previous emails, phone calls, chats with its customers). Therefore, the lack of internal data is a more crucial barrier to adoption than the availability of external data.

Finally, breaking down AI advancement into its separate steps is also crucial in terms of the skills necessary for AI advancement. While the number of academic AI researchers is important for pushing AI research forward, the overall number of awarded AI and data engineering degrees (PhD and Masters) is more relevant for supporting AI development. Finally, when it comes to integrating AI into regular non-AI businesses, the availability of computer science, IT infrastructure and data management skills in the workforce are the relevant barrier.

Table 1: Production chain of AI and metrics for tracking AI advancement

	AI research	AI development	AI adoption
Who	Universities, private research laboratories	Technology companies (big tech & AI start-ups/scale-ups)	(Non-AI) Firms across all sectors of the economy
What	Discovering new techniques to make decisions based on data	Developing an AI product or service for a business application	Buying an AI product or service for use in production processes or service delivery
Examples	Discovering new language processing techniques	Developing AI product for screening CVs	Buying CV-screening algorithm for use in hiring process
	Discovering new image recognition techniques	Developing AI product for detecting quality deviations	Buying quality control algorithm for use in manufacturing process
Importance for EU policy	Priority-setting Relevance & applicability	Strategic autonomy Standard-setting	Productivity Competitiveness
Metrics of success			
	Number of paper/ conference citations	Number of AI start-ups Number of AI unicorns Number of AI patents	% of firms adopting AI
Barriers to success			
Skills	Academic AI researchers	AI PhD's & Master degrees	Computer science degrees
Financial constraints	Public funding	Venture capital	R&D subsidies or tax deductions
Data availability	External (public & private) data for testing techniques	External (public & private) data for training models	Internal data for finetuning models

Source: Bruegel.

The breakdown of AI advancement we have set out is partly reflected in the European Commission's proposed digital goals for 2030 (European Commission, 2021). In the area of the 'digital transformation of businesses', the Commission wants to double the number of EU unicorns, which reflects its goals on AI development in Europe. On AI adoption, the Commission aims for 75 percent of companies to take up advanced technologies including artificial intelligence (AI), cloud computing and big data analysis[3]. While the number of EU AI unicorns can be easily counted, reliable estimates of AI adoption are much harder to collect (Box 1).

3 The Commission even plans to name and shame lagging countries that fail to achieve their targets, in order to motivate national governments to take action (Prpic, 2014). See also Valentina Pop, 'Europe Starts Feeling Pinch from Its Green Transition', *Financial Times*, 13 September 2021, https://www.ft.com/content/99c159ae-274f-4ab4-b273-431c58c23355.

Box 1: Measure what you treasure: data on AI adoption

It is unclear what the current state of AI adoption in Europe actually is, as estimates of the use of AI by European companies differ widely. Even two European institutional sources give very different rates of 7 percent adoption (Eurostat, 2021) to 42 percent (European Commission, 2020). Differences in methodology do not fully explain the differences in estimates, as both surveys have the same time and geographical coverage and aim for representative sampling design. Eurostat's survey excludes financial sector companies and micro-enterprises with fewer than 10 employeesoyees, but these exclusions do not explain the difference as micro-enterprises generally have lower adoption rates (so excluding them would bias the average upward) while financial sector adoption hovers around the average. The European Commission (2020) survey's final sample size is much smaller than Eurostat's (9640 compared to 142,000), but the survey still designed to be representative in terms of countries and firm size.

It is more likely that the gap in estimated adoption of AI results from differences in response rates to the two surveys. The response rate to the Eurostat survey ranged from 31 percent in Germany to 98 percent in Lithuania, reaching a respectable average of 74 percent and a median of 80 percent across countries. The response rate to the European Commission (2020) survey however ranged from 5 percent and 19 percent at country level, averaging 7 percent. This implies that the adoption rates given in the latter are biased upwards, as firms that were already using AI were more likely to participate.

After accounting for the bias induced by non-responses, the remaining differences in the estimates of AI adoption can be explained by the differences in the definition and taxonomy of AI in the survey questions. The Eurostat survey asked about the following four types of AI:

1. Analyse big data internally using machine learning (ML);
2. Analyse big data internally using natural language processing (NLP), generation or speech recognition;
3. Use of a chat service where a chatbot or virtual agent replies to customers;
4. Use of service robots (autonomous machines).

These categories focus on a limited set of specific AI applications, and are not mutually exclusive either. NLP (type 2) is a form of machine learning (type 1), and training chatbots (type 3) requires fine-tuning NLP algorithms on internal data (type 2). Finally, the use of service robots (type 4) typically requires the use of internal data using machine learning (type 1) to train or fine-tune the robot.

The European Commission (2020) survey takes a wider approach and asks about the use of ten different categories of AI:

1. Speech recognition, machine translation or chatbots (NLP);
2. Visual diagnostics, face or image recognition (computer vision);
3. Fraud detection or risk analysis (anomaly detection);
4. Analysis of emotions or behaviours (sentiment analysis);
5. Forecasting, price optimisation and decision-making using ML algorithms;
6. Process or equipment optimisation using AI;
7. Recommendation and personalisation engines using AI;
8. Process automation using AI, including warehouse automation or robotics process automation;
9. Autonomous machines, such as smart and autonomous robots or vehicles;
10. Creative and experimentation activities, such as virtual prototyping, data generation, artificial music or painting.

While this taxonomy does a better job of setting out mutually exclusive categories and covering a wider range of AI applications, it is still a combination of technologies (for example, NLP and computer vision) and business applications (for example, forecasting and risk analysis).

When comparing pair-wise estimates of similar categories, the differences between the two surveys are smaller: NLP reaches about 3 percent in the Eurostat survey (types 2 and 3) and about 10 percent in the European Commission survey (type 1), while autonomous robots reach 2 percent in the Eurostat survey and 9 percent in the European Commission survey. However, a sizeable difference still remains, which we attribute to the non-response issue discussed above. Nonetheless, the EU should develop a standard definition of AI and its subcategories, and explicitly differentiate between technologies and business applications (Hoffmann and Mariniello, 2021).

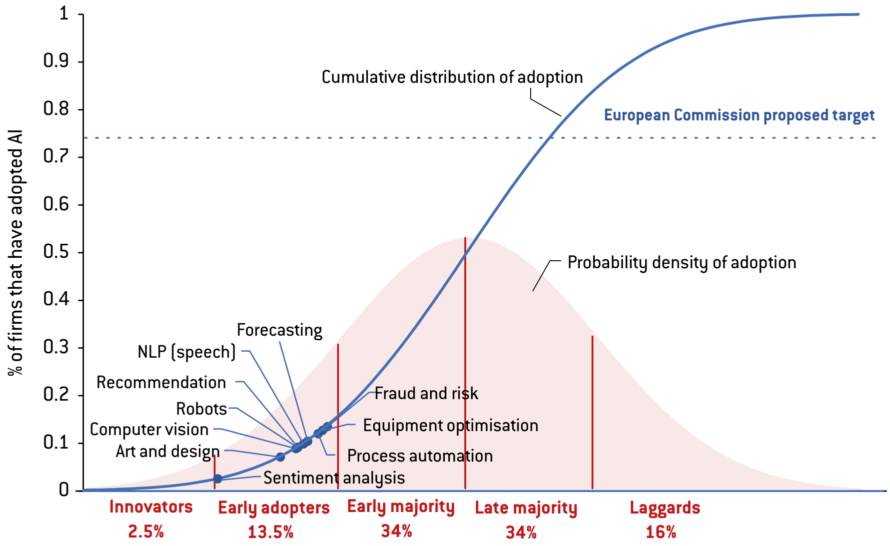
3 The state of AI adoption in Europe

According to Rogers's Diffusion of Innovations (DOI) theory, new technologies spread across an economy incrementally, rather than instantaneously (Lundblad, 2003; Rogers, 1983). The decision to adopt entails costs and risks. It requires upfront investment in infrastructure and the technology itself, while the potential returns are unknown. Moreover, deployment implies costly operational and organisational adjustments, which not every organisation can make at the same time.

Economies therefore consist of different group of adopters. Innovators (2.5 percent of firms), usually venturesome and large organisations, introduce the innovation to the economy. Early adopters (13.5 percent of firms), which are open to change but more risk averse than innovators, are next in line to adopt. Their decision serves as a signal to the rest of the economy that reduces uncertainty around the investment, and is key to achieve critical mass. The early majority (34 percent) are more prudent but still adopt the innovation just before the average firm does. At this point, the technology has dispersed throughout half of the economy. The second half consists of the late majority (34 percent) and laggards (16 percent), which are considered sceptical or even suspicious of innovations. By the time laggards adopt, innovators may have already adopted the next innovation.

Notwithstanding the shortcomings of the European Commission (2020) survey in terms of response rate (and acknowledging its upward bias in estimating adoption, Box 1), it still provides the best data source for comparing the uptake of different types of AI across the economy, since it covers such a wide range of applications. Figure 1 shows that firms are quicker to adopt AI in 'traditional' applications of data-driven intelligence such as fraud and risk analysis, equipment optimisation and process automation – applications that were previously driven by classical statistics and programmable logic controllers, but which are now being supplemented by machine learning. Newer domain applications including speech recognition (NLP) and image recognition (computer vision) are still in the earlier phases of adoption, while the most fringe applications, including sentiment analysis, art and design, are just crossing over from the innovators to the early adopters.

Figure 1: Diffusion of AI technologies in Europe



Bruegel based on Rogers (1983) and European Commission (2020).

Diffusion across industries of these specific sub-categories of AI also shows clear clusters (Table 2). The primary and secondary sectors (agriculture and manufacturing) mainly use AI in production and process applications (robots, process automation and equipment optimisation). Tertiary sectors use relatively more NLP, recommendation engines and the more creative and innovative AI applications for sentiment analysis, art and design. The Eurostat data covers fewer categories of AI, but also shows that service robots (type 4) are taken up mostly in the manufacturing sector, while the ICT sector has a very strong lead in all other types (machine learning, NLP and chatbots).

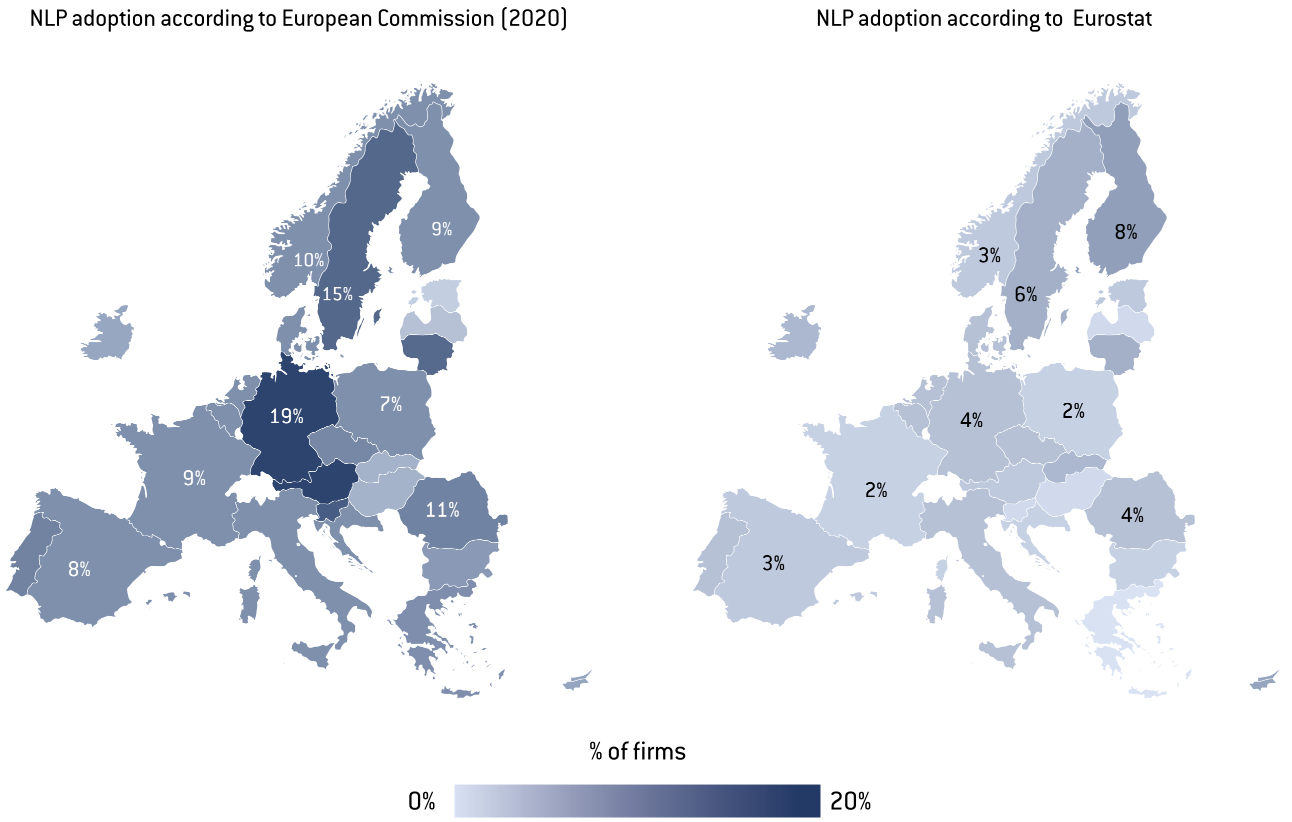
Table 2: Adoption of AI applications by sector and type of AI

% of firms adopting an AI application of type …	All sectors	Agriculture, forestry & fishing	Manufacturing	Construct., waste, water & electricity	Trade, transport, hospit. & recreation	IT, finance, real estate & scientific	Education, health & social work
Fraud and risk	13%	15%	13%	10%	13%	15%	16%
Equipment optimisation	13%	13%	15%	11%	11%	13%	14%
Process automation	12%	14%	17%	9%	10%	13%	13%
Robots	9%	18%	15%	8%	7%	7%	10%
Computer vision	9%	14%	8%	9%	8%	11%	9%
Forecasting (non-stats)	10%	10%	10%	8%	12%	10%	10%
NLP (speech)	10%	4%	8%	8%	9%	14%	15%
Recommendation	9%	7%	8%	7%	9%	11%	10%
Art and design	7%	9%	9%	8%	5%	8%	11%
Sentiment analysis	3%	3%	1%	2%	2%	4%	5%

Source: Bruegel based on European Commission (2020). Note: The table shows the percentage of firms that report that they are currently using an AI application of a specific type by sector. The colours reflect the intensity of adoption: green means high adoption, red means low adoption. The clusters are described in the text above, the colours show a pattern of clusters (see text above).

The data suggests that the EU is still in the early stages of AI adoption. This is true for most individual European countries as well. Since both the European Commission (2020) survey and the Eurostat data include NLP as a sub-category of AI[4], we compare in Figure 2 the estimate of NLP adoption across countries from both data sources. Again, adoption is estimated at a higher rate in the European Commission (2020) survey, ranging from 2 percent in Malta to 19 percent in Germany and Austria, while the Eurostat data ranges from 1 percent in Greece to 8 percent in Finland. Surprisingly, the correlation of the two data series at country level is -0.02, meaning the two data series bear almost no resemblance to each other. While some countries, such as Lithuania and Sweden, score high in both series, others like Malta find themselves at different ends of the distribution.

Figure 2: Diffusion of natural language processing across European countries, comparison of European Commission survey and Eurostat data



Source: Bruegel based on European Commission (2020) and Eurostat (2021). Note: The maps show the percentage of firms that report that they are currently using an NLP application by country. From the European Commission survey we use type 1 (NLP & chatbots), from the Eurostat data we use the sum of type 2 (NLP) and type 3 (chatbots).

Finally, as Rogers's DOI theory predicts, adoption indeed correlates strongly with firm size. Using the same sub-category of AI as before (NLP[5]), the European Commission survey data finds adoption by large firms (more than 250 employeesoyees, 16 percent) to be twice as high as by small firms (fewer than 50 employeesoyees, 8 percent), and in the Eurostat data adoption by large firms (11 percent) is almost four times higher than by small firms (3 percent).

4 Comparing type 1 NLP & chatbots from European Commission (2020) with type 2 NLP + type 3 chatbots from Eurostat (2021).

5 Comparing type 1 NLP & chatbots from European Commission (2020) with type 2 NLP + type 3 chatbots from Eurostat (2021).

4 Drivers of technology adoption

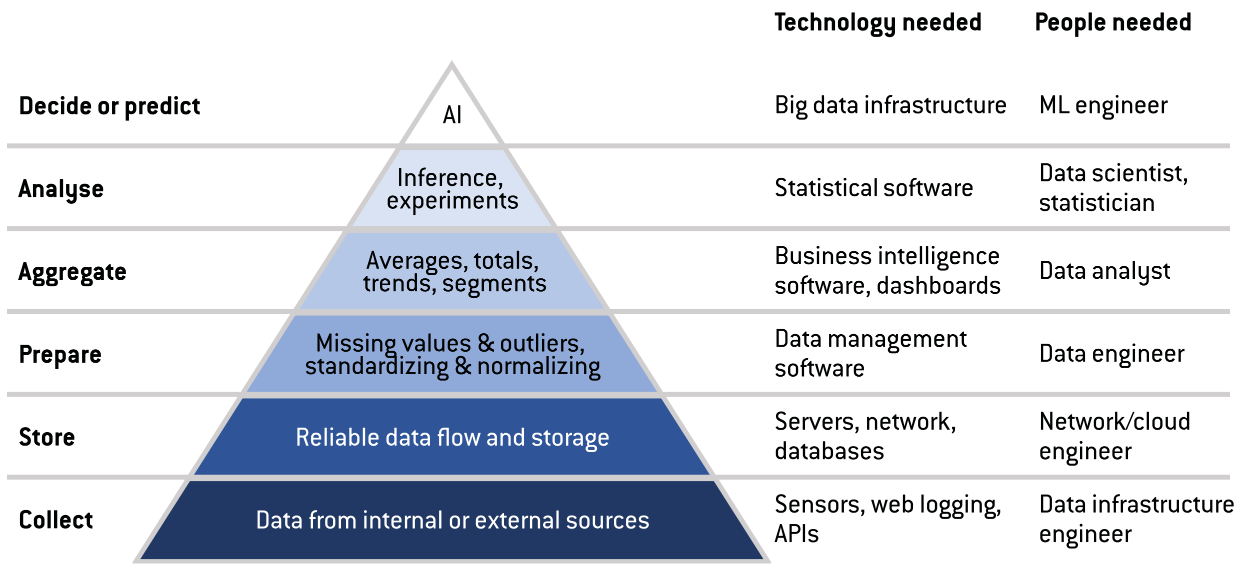
4.1 Three factors that influence technology adoption

Technology adoption decisions at the firm level are influenced by technological, organisational and environmental factors (Baker, 2012; Tornatzky *et al*, 1990).

The technological context is determined by comparing the firm's own state of technological development to the technological frontier (Oliveira and Martins, 2011). This gap comprises different types of innovations, which can be ranked by the degree of change their adoption requires, from incremental to synthetic to radical (Baker, 2012). Incremental technologies require the least amount of adjustment, and are comparable to upgrading software or equipment that is already in use. Innovations that provoke so-called synthetic change are those where existing technologies are combined in a new way to create innovative applications and use cases. Radical or disruptive technologies lead to major changes in processes and technologies that demand quick and decisive adoption decisions in order to maintain competitiveness. Those kinds of innovations can be competence-enhancing or destroying, meaning that they either build on existing expertise to augment and improve processes, or that their adoption renders existing expertise and technologies obsolete. Intuitively, organisations tend to adopt incremental and synthetic technologies more easily and frequently than disruptive ones.

This technological readiness is especially important for AI, since digital technologies are hierarchical, meaning the use of AI systems requires other 'lower' technologies such as data storage and computing power (Zolas *et al*, 2020). Without a way to collect, store, move and transform data, companies cannot begin to learn from their data or use it to support intelligent decision making (Figure 3). The importance of technological readiness is also reflected in the split of AI adoption by type of application (Figure 1), which shows that firms are more likely to build AI on top of existing data-driven applications than to invest in completely new applications. Besides compatibility with existing systems, firms base adoption decisions on a technology's relative advantage over technology they already have, and the visibility of these improvements (Lundblad, 2003). A high degree of triability, ie the ability to experiment with an innovation before commitment, reduces uncertainty and facilitates adoption. Finally, simple technologies are adopted more easily, as complex technologies require more organisational adjustments (Lundblad, 2003).

Figure 3: The hierarchical nature of digital technologies



Source: Bruegel based on Monica Rogati, 'The AI hierarchy of needs', *Hackernoon*, 12 June 2017, available at https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007.

Organisational characteristics that affect technology adoption relate to leadership, structure and networks (Lundblad, 2003). Positive attitudes towards change among management facilitate adoption. Similarly, decentralised power structures and lower levels of formality stimulate innovation, as do high levels of knowledge and staff expertise. Some organisational slack (excess capacity) is also helpful (Baker, 2012). Finally, closely-knit (in)formal networks, both intra- and inter-firm, are associated with faster technology adoption. The effect of firm size on technology adoption is ambiguous. In theory, firm size serves as a proxy for resource endowment (financial, but more importantly, skilled labour) and risk-taking capacity, both of which are conducive to technology adoption (Baker, 2012). Empirical evidence on e-business adoption, however, shows mixed results, fuelling the argument that the hierarchy, bureaucracy and structural inertia associated with large corporations may also slow effective technology adoption (Oliveira and Martins, 2010; Zhu *et al*, 2006b) see section 3.2 for more detail on AI adoption by European SMEs).

The environmental context describes the setting in which a firm conducts its business, and includes the market structure, external factor endowment and policy environment (Baker, 2012). Competition incentivises technology adoption, as does the adoption of an innovation by trading partners, by raising the benefits of adoption (Bloom *et al*, 2016; Oliveira and Martins, 2011). Similarly, innovation happens at a faster rate in growing industries. External environmental constraints on technology adoption are the availability of skilled labour and suppliers of technology, as well as access to financing. Government policy, such as regulation or tax incentives, can be a promoter or inhibitor of innovation. Finally, social and cultural determinants, including consumer preferences and competitive trends, exert pressures on organisations (Oliveira and Martins, 2011). As a result, firms in the same sector tend to become more similar as organisations mimic the industry leader (DiMaggio and Powell, 1983).

4.2 The significance of firm size: adoption of AI by European SMEs

The theory outlined in section 3.1 predicts two opposing forces that grow with firm size: that increasing resource endowment and risk-taking capacity facilitate adoption by large firms, while bureaucracy and the structural inertia of large firms slow down adoption. Looking at both data sources (European Commission, 2020, and Eurostat, 2021), it seems that the first effect largely dominates.

European Commission (2020) shows a positive correlation between firm size and AI adoption, with the adoption rate increasing by 2 percentage points on average with each jump in firm-size category. However, the correlation is only significant for the largest two categories of firms: the rate of adoption by large firms (more than 250 employeesoyees) is 5.7 percentage points higher than by micro firms (fewer than 5 employeesoyees), and the rate of adoption by medium-sized firms (49-250 employeesoyees) is 2.3 percentage points higher than by micro firms, while there is no statistical difference between the rate of adoption by micro firms and small firms (5-9 employeesoyees).

In terms of the diffusion by type of AI application (Table 3), large corporations lead the way across all types of AI, and medium sized firms follow steadily, yet we see two different patterns emerging among micro firms and small firms. While six out of 10 technologies still show a steady increase in adoption with firm size among micro and small firms, the other four technologies show a U-shaped trend, with micro firms actually adopting at a faster rate than small firms[6].

6 Since we do not have data on the variation within these groups (by type of AI and firm size), we cannot calculate whether the differences at this level of aggregation are statistically significant.

Table 3: Adoption of AI applications by firm size and type of AI, European Commission data

	All firms	Micro 5-9 employees	Small 10-49 employees	Medium 50-249 employees	Large >250 employees
Fraud and risk	13%	13%	11%	15%	21%
Equipment optimisation	13%	12%	11%	15%	17%
Process automation (RPA)	12%	10%	11%	14%	21%
Forecasting (non-stats)	10%	9%	10%	13%	15%
NLP (speech)	10%	9%	8%	12%	16%
Recommendation engine	9%	9%	8%	10%	12%
Robots	9%	7%	8%	11%	15%
Computer vision	9%	8%	8%	9%	12%
Art and design	7%	7%	7%	7%	10%
Sentiment analysis	3%	2%	2%	3%	4%

Source: Bruegel based on European Commission (2020). Note: The table shows the percentage of firms in each size category that report they are currently using an AI application of a specific type. The colours reflect the intensity of adoption: green means high adoption, red means low adoption, the colours show a pattern of clusters (see text above).

The Eurostat data also shows a clear increasing trend of AI adoption across firm size, with large firms adopting at a rate that is three to five times faster than small firms, which is an even more rapid increase than shown in European Commission (2020). Since Eurostat excludes micro enterprises (<10 employeesoyees), we cannot detect any non-linearities at the lower end of the size distribution.

Table 4: Adoption of AI applications by firm size and type of AI, Eurostat data

	All firms	Small 10-49 employees	Medium 50-249 employees	Large >250 employees
Analyse big data internally using ML	2%	2%	4%	11%
Analyse big data internally using NLP	1%	1%	2%	5%
Chatbot or a virtual agent replies to customers	2%	2%	3%	6%
Service robots	2%	2%	4%	11%

Source: Bruegel based on Eurostat (2021). Note: see table 3.

Overall, based on the two data sources, we cannot reject the hypothesis that the two opposing forces stemming from firm size result in non-linearities in adoption across firm size. However, it does seem that the endowment effect largely dominates over the inertia effect, leading medium-sized and large firms to adopt AI more rapidly than small firms.

4.3 Lessons from previous and foreign innovation waves

The last big innovation comparable to today's AI was the adoption by firms of digitisation and e-business operations in the early 2000s. Empirical findings on adoption drivers and barriers for European firms back then may help inform policymakers today and help to facilitate AI take-up. For example, organisations with skilled staff and good IT infrastructure adopted e-business operations faster than others (Oliveira and Martins, 2010). Importantly, a major concern guiding e-business adoption was security, in particular in relation to data privacy and online fraud, paired with uncertainty about the legal framework (Zhu *et al*, 2006a, 2006b). In early stages of diffusion, the lack of e-business adoption by trading partners strongly held back firms' own e-business use. Limited consumer willingness to engage in online activities constrained expected returns and therefore had similar effects (Zhu *et al*, 2003).

Comparable constraints likely hinder AI adoption in the EU today, since AI serves as both an internal operational and an external customer-facing technology. While empirical evidence on drivers and barriers to AI adoption in Europe is still scarce, we can learn from experiences studied in other regions.

A study on smart manufacturing technology adoption by Iranian and Malaysian SMEs showed that, given the extensive changes in workflows, operational processes and structures required for its implementation, compatibility of the system with organisational goals and strategies was a crucial determinant of adoption. The availability of a strategic roadmap was described as "*one of the most significant discriminators between adopters and non-adopters*" (Ghobakhloo and Ching, 2019: 12). The study also found that external pressure from the government, customers or suppliers positively affected smart-tech adoption decisions. While competitive pressure did not impact the adopt-or-not decision, it did affect the level of investment for those that did adopt.

Big data analysis adoption by Chinese logistics and supply-chain firms was found to be primarily driven by the technology's economic (cost-saving or risk-minimising) benefits and top management support (Lai *et al*, 2018). High-level management involvement ensured that sufficient financial and administrative resources were devoted to developing analytics capabilities (in terms of personnel and infrastructure). This effect of management support increases with big data analysis adoption by suppliers and competitors, and with supportive government policy. This is likely because strategic management is sensitive to regulatory changes and shifts in market structure.

5 Barriers to AI adoption

5.1 Reported barriers to AI adoption in the EU

The empirical evidence we have outlined substantiates the theoretical importance of the external and internal drivers and barriers to firms' technology adoption decisions. European Commission (2020) asked firms which factors they consider as major and minor obstacles to AI adoption. While the low response rate to this survey seriously biases its estimates on adoption, this doesn't reduce the relevance of the reported barriers. Given that the survey was more likely to be answered by firms that recently adopted AI or are considering AI adoption, these firms probably have a good understanding of the barriers they currently or have recently faced.

Skills and financial constraints are the leading reported barriers across adopters and non-adopters (adding up major and minor barriers), with about 80 percent of respondents citing a lack of skills in their internal workforce and in the external labour market, as well as the high cost of buying the technology and adapting their operational processes around AI – which includes getting workers on board (Hoffmann and Nurski, 2021). Relating to the previous state of digitisation, companies perceive their lack of (compatible) IT infrastructure as a greater barrier than their lack of data (Figure 4). However, without the proper IT infrastructure, firms cannot start collecting and storing the data which the basis for adopting AI (Figure 3).

There are significant differences between AI-adopters and non-adopters in their current endowments of IT and labour resources, confirming the importance of the previous state of digitisation: non-AI adopters report a higher degree of insufficient IT resources (74 percent vs 68 percent), lack of internal data (58 percent vs 52 percent) and lack of skills among existing staff (81 percent vs 76 percent). This lagging digitisation is reflected in other data sources as well: despite being relatively established systems, only 33 percent of European companies use customer relationship management (CRM) systems, and 36 percent use enterprise resource planning (ERP) software[7]. And, while 36 percent of enterprises invest in cloud computing services, only 12 percent of firms perform any kind of big data analysis[8]. Despite being a top

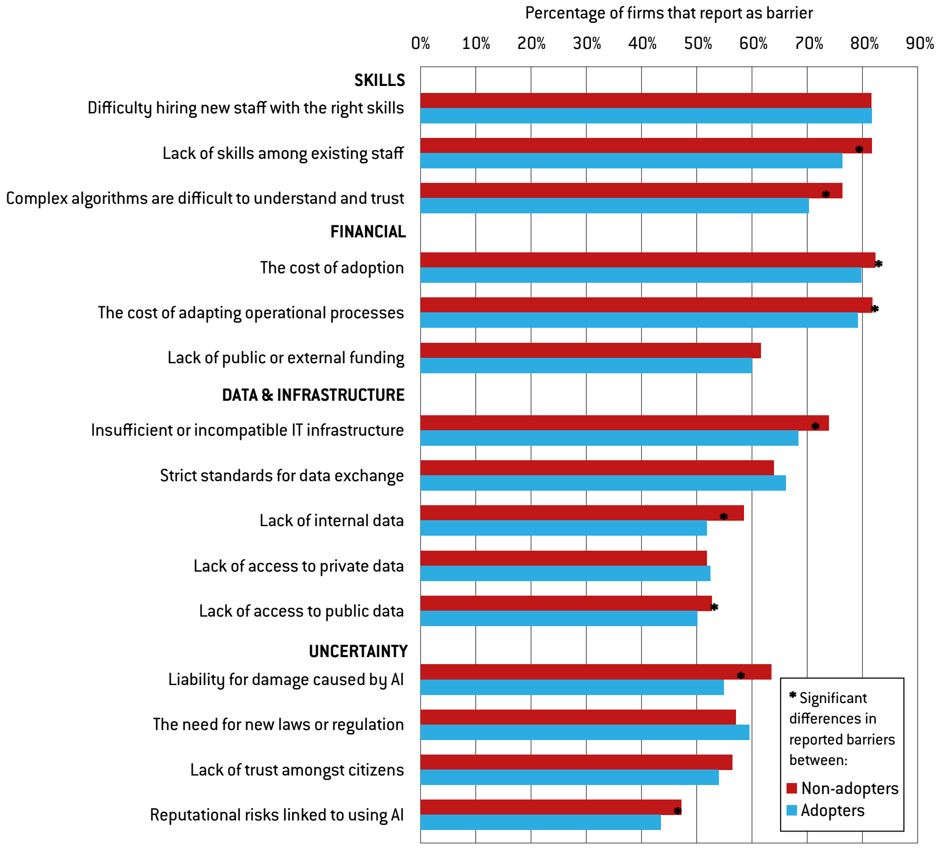
7 Eurostat, isoc_ci_eu_en2 and isoc_eb_iip.

8 Eurostat, isoc_cicce_use and isoc_eb_bd.

priority of the European Commission, an analysis of spending on the digital transformation in the EU recovery programme has concluded that investment in business digitalisation still falls far short of meeting existing funding gaps (Darvas *et al*, 2021).

Finally, non-adopters differ significantly from adopters in their perception of legal and regulatory uncertainty as a barrier to adoption. Non-adopters are more concerned about the liability risk for damage caused by AI (63 percent vs 55 percent) and the reputational risk linked to using AI (47 percent vs 43 percent), supporting the claim that reducing uncertainty is a crucial element in pushing adoption from the early adopters to the early majority, and to achieve critical mass (Rogers, 1983) (Figure 4).

Figure 4: Non-adopters are held back most by internal barriers

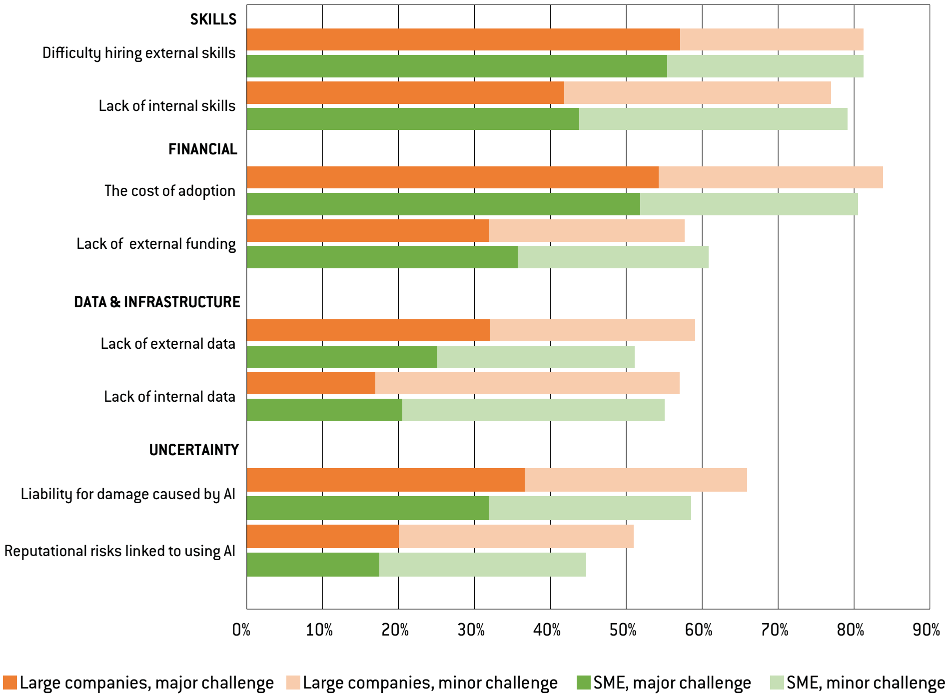


Source: Bruegel based on European Commission (2020), adding up 'major' and 'minor' obstacles reported by firms in the survey.

Given the slower rate of adoption by European SMEs, differences in reported barriers can be analysed by firm size. A first observation is that most differences can be found between large enterprises (more than 250 employeesoyees) and SMEs (fewer than 250), while there is not much difference in the barriers reported by micro, small and medium-sized firms.

SMEs report approximately the same skill barriers as large enterprises, although large firms perceive a slightly greater lack of skills in the external labour market, while SMEs perceive a slightly greater lack of skills in their internal workforces. The same pattern can be observed among the data barriers: large firms worry mostly about lack of access to external data, while SMEs report a lack of internal data. Both patterns in the skill and data barriers point to the lagging internal digitisation of European SMEs. Finally, in terms of financial constraints, the lack of public or external funding is a higher barrier for SMEs, pointing to the lower resource endowment and more binding credit constraints SMEs face.

Figure 5: SMEs report higher internal barriers, while large enterprises report higher external barriers in terms of skills and data



Source: Bruegel based on European Commission (2020).

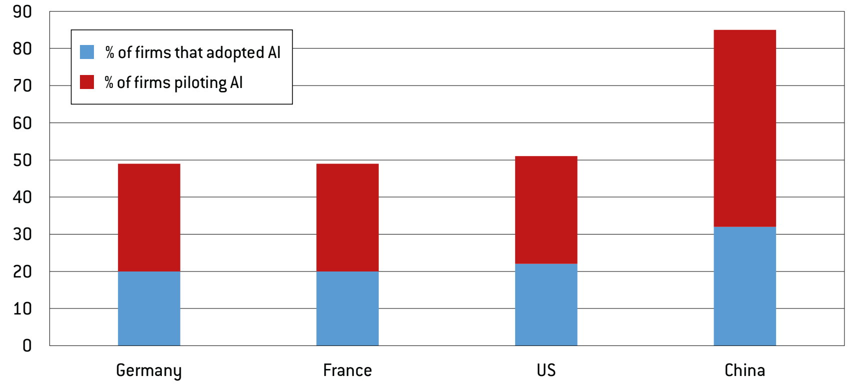
5.2 Comparing the EU to the US and China

The potential of AI to boost productivity is today internationally recognised. It implies a competitive advantage for those businesses that manage to leverage AI's potential at scale early on. Aside from the EU, many economies have published national AI strategies and plans to foster AI advancement, in particular the US and China (Zhang *et al*, 2021). Given this international attention, we aim to understand how the EU is doing in comparison with other economies in terms of AI adoption, and in particular whether the barriers we describe are universal, or whether they are holding back EU companies in particular.

Regional differences in AI adoption

As we have noted, the measurement of AI adoption is highly dependent on the definition and taxonomy used. There is no common international metric that allows the exact measurement and comparison of AI adoption rates in different countries. Based on a small-sample international survey of about 2700 executives, Boston Consulting Group provided an estimate of AI diffusion in the private sectors of France, Germany, the US and China, among other countries (Figure 6) (Duranton *et al*, 2018). AI adoption appears to be significantly more advanced in China than Western economies, while the gap between the US and EU countries appears relatively small. Importantly, the speed of diffusion seems faster in China, with the majority of firms already piloting AI functions, which implies a widening of the gap in the future.

Figure 6: Estimated AI adoption rates, 2018



Source: Bruegel based on Duranton *et al* (2018).

While we believe the exact level of the estimates should not be taken at face value, the adoption rates in Duranton *et al* (2018) nonetheless provide some valuable insights. First, their numbers confirm that the 'race' for leadership in AI has several aspects. AI adoption is important, but is quite distinct from AI research and development, in which the US is still widely considered to be in a leading position (Brattberg *et al*, 2020; Bughin *et al*, 2019; Zhang *et al*, 2021). Second, the estimates corroborate the findings of a growing number of reports that the EU is beginning to fall behind in the international competition for AI leadership.

Regional differences in barriers

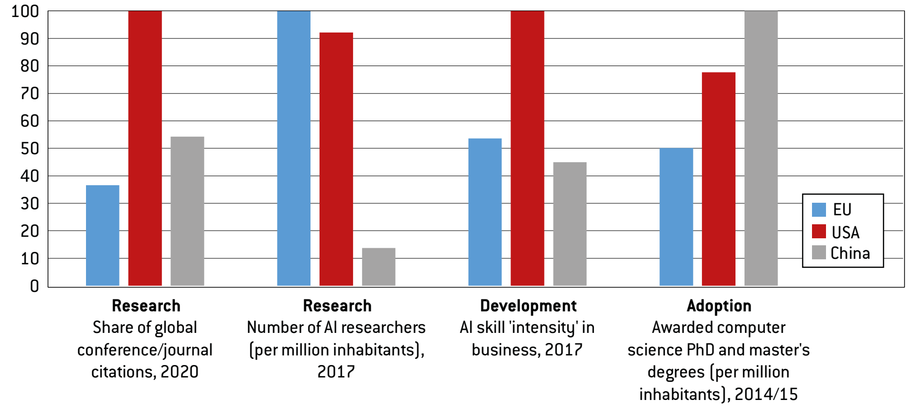
To investigate how Europe-specific the barriers to adoption identified by European firms are, we compare key indicators for the EU, US and China that relate to the availability of skills, data, funding and regulation. Since different types of skills, data and funding are required to advance in AI research, development and adoption, a label indicates which step is primarily affected by the indicator we present. To enhance readability and comparability, the data is indexed to 100 for the highest value among the three economies.

On skills availability, the EU appears well-equipped for frontier AI research, thanks to an extensive talent pool of academic researchers (Figure 7). However, the relative international impact of EU-based AI studies appears to be declining, surpassed by China, which has doubled its share of global citations since 2013 (Zhang *et al*, 2021). Crucially, the EU appears unable to leverage this expertise for AI adoption by the private sector. The indicator for skill intensity in business is based on the average number of AI researchers employeesoyed in the economy's top AI firms, which in the US is almost twice as high as in the EU (Castro *et al*, 2019)[9]. Given the low AI adoption rate among US firms (Figure 6) it may well be, however, that AI research skills in the US private sector are highly concentrated in a few industry leaders, a hypothesis for which Wang *et al* (2021) recently found evidence.

In addition, firms' adoption of AI technology likely depends on being able to recruit capable computer scientists, programmers and data engineers, who can tailor existing algorithmic and deep-learning software to practical operational needs. A proxy for the availability of such skills in the labour market is the number of computer science degrees awarded per million inhabitants (Figure 7, column 4). Although the data is slightly dated, it indicates that EU enterprises may find the recruitment of the right skills much more difficult than their US and, in particular, Chinese counterparts.

9 The Chinese estimate is based on only one firm that fulfilled the criteria for top AI firm in 2017, Huawei, which is why their estimate may not be too comparable.

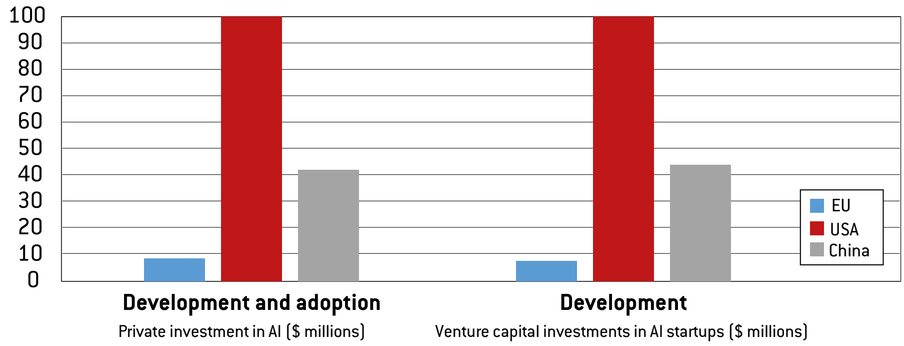
Figure 7: Skill constraints on AI advancement



Source: Bruegel based on Anderson *et al* (2020), Castro *et al* (2019) and Zhang *et al* (2021).

Second, EU companies lack funding compared to their Chinese and American counterparts, which affects both AI development and adoption (Figure 8). Importantly, the gap with the US and China in this respect is considerably larger than for the other indicators. Private investment in AI in the EU represents less than 25 percent of that in China and less than 10 percent than that in the US, a pattern mirrored in venture capital for AI startups.

Figure 8: Financing constraints on AI advancement

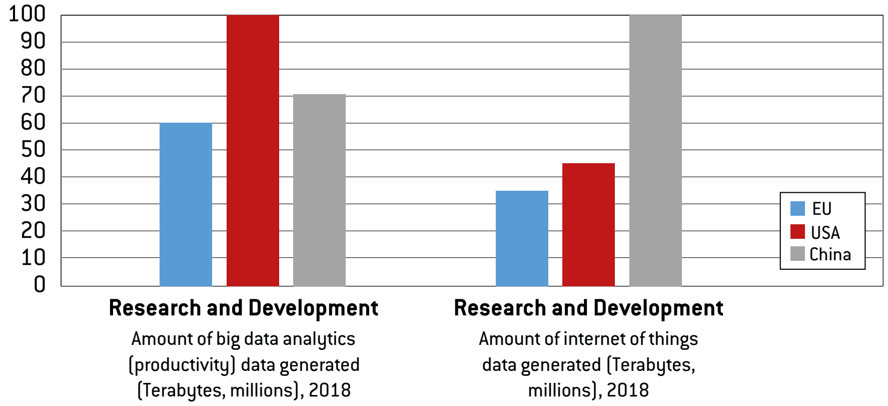


Source: Bruegel based on OECD.AI (2021) and Zhang *et al* (2021).

A third aspect to consider is data availability. In the European Commission (2020) survey, EU firms identified a lack of internal data and insufficient access to public and private datasets as barriers to AI adoption. Data limitations prevent us from comparing business data availability or public records accessibility. Instead, Figure 9 compares the generated amounts of big data stemming from internet of things devices and other productivity data. Machine-generated data and technical, operational business data can be used to train ML algorithms for example in manufacturing or retail. Figure 9 shows that data generation in the EU appears to be trailing behind the US and China, which we believe could be driven by the low levels of digitisation in business, administration and even infrastructure in the EU. Importantly, looking at data generation alone does not take into account the accessibility of these datasets.

The EU has made efforts to improve the availability of such data across member-state borders. Its directive on open data and the re-use of public sector information in 2019 (Directive (EU) 2019/1024) addressed in particular the availability of public (anonymised) data sources, also known as 'open data' initiatives. With respect to non-personal information like machine-generated data, the Commission has taken action to improve cross-country accessibility via a framework for the free-flow of non-personal data in the EU (Regulation (EU) 2018/1807). It remains to be seen how effective these initiatives will be in making high-quality data available.

Figure 9: Data constraints on AI advancement



Source: Bruegel based on Castro *et al* (2019).

Finally, none of the three economies has so far put in place comprehensive regulations on AI, even though proposals are advancing in each of the jurisdictions. As such, regulatory uncertainty with respect to the use of AI applications, for example in terms of liability for damages caused by AI, is likely similar across all three regions. The degree of clarity and specificity of the emerging legislative environment will play a major role in reducing this uncertainty in the private sector and stimulating AI adoption.

Importantly, emerging AI policies build on existing data protection laws. In comparison to the EU's established GDPR, such regulation is nascent in China[10], and fragmented in the US[11]. Despite criticism that strict data privacy laws such as the GDPR stifle AI advancement, this link is not established and the overall impact on AI adoption is likely ambiguous. Regulation might raise barriers by aggravating compliance and bureaucratic loads. However, it provides regulatory certainty which is important for innovation. The GDPR is widely seen as successful in establishing global data privacy norms in the digital world (Brattberg *et al*, 2020). Through its principles of accountability and transparency, the GDPR will likely play an important role in building citizens' trust and acceptance of future AI technology and may even be seen as a strong foundation on which to build future AI regulation, which puts the EU in a leading position compared to the US and China (Brattberg *et al*, 2020; MacCarthy, 2020).

In conclusion, comparing international differences, it appears that lack of financing is the most crucial barrier, followed by the limited transfer of academic AI talent into practical AI and data skills in private businesses. In terms of data availability, policymakers can focus on opening up public (anonymised) data and stimulating the collection of non-personal business data by private businesses. Alleviating these most pressing constraints in terms of skills, financing and data could go a long way to promote AI advancement in Europe, without weakening the EU's first-rate privacy protection.

10 See Scott Pink, 'What China's New Data Privacy Law Means for US Tech Firms,' *TechCrunch*, 10 September 2021, https://social.techcrunch.com/2021/09/09/what-chinas-new-data-privacy-law-means-for-us-tech-firms/, and Eva Xiao, 'China Passes One of the World's Strictest Data-Privacy Laws,' *Wall Street Journal*, 20 August 2021, https://www.wsj.com/articles/china-passes-one-of-the-worlds-strictest-data-privacy-laws-11629429138.

11 See Thorin Klosowski, 'The State of Consumer Data Privacy Laws in the US (And Why It Matters),' *NYT Wirecutter*, 6 September 2021, https://www.nytimes.com/wirecutter/blog/state-of-privacy-laws-in-us.

6 Policy recommendations for supporting AI adoption in Europe

In order to accelerate the roll-out of AI technology across the EU, policymakers should take action to alleviate constraints to adoption faced by firms, both in the environmental context – skills, financing and regulatory uncertainty – and in the technological context – data availability, basic digitisation of businesses and technological uncertainty.

In terms of the environmental context, the recruitment of skilled staff and upgrading the skills of existing staff is considered a major obstacle by the majority of firms. International comparisons confirm that despite the EU's large number of academic AI researchers, it doesn't deliver the same amount of skilled labour to private firms, resulting in a lack of skilled data scientists that can put AI to practical commercial use. This suggests that the labour market is a binding constraint on AI adoption and a crucial policy field for the EU and member states. Improving opportunities for adult learning (both for the employeesoyed and the unemployeesoyed) and making data skills part of more educational curriculums are the first steps to take.

Lack of financing is a second major barrier to AI adoption as both the acquisition of the technology and the adaptation of operational processes around AI are costly. SMEs in particular find the lack of external or public funding troublesome. International comparisons often focus on the EU's huge lack of venture capital investments in AI, which is crucial for AI development. But to stimulate adoption of AI among regular non-tech firms and SMEs, governments might better look towards tax deductions or subsidies that support the acquisition of AI technology and its related services.

Legal and regulatory uncertainty, including around the liability for damages caused by AI, is a third obstacle that policymakers should address. Firms can only begin to assess potential risks and returns on investment in AI technology in a stable and predictable regulatory environment. Despite having a clear regulatory foundation in terms of data privacy, the lack of legal certainty in the EU with respect to the use of AI delays the absorption of existing technologies in the private sector. Policymakers therefore need to draw up a clear, future-proof regulatory framework for the use of AI in business.

In terms of the technological context, given that algorithms need data and computing power, Europe's lagging digital transformation is a serious barrier to AI adoption. While access to external (private and public) data is necessary for AI research and development, internal data is more crucial for AI adoption by non-R&D-firms. SMEs especially are running behind in basic digitisation of internal processes, leading to a lack of internal data on which AI algorithms can be fine-tuned to their specific businesses. Governments should therefore first promote the digitisation of business (including the collection of business data) and support the investments needed to improve technological readiness necessary for AI adoption.

Reducing the technological uncertainty surrounding the economic returns to AI by increasing its triability also accelerates its adoption. This may be a way to accelerate the uptake of pilot programmes by European firms, and narrow the increasing adoption gap with China. Governments can play a role in this by facilitating the provision of AI 'sandboxes'[12] so companies and public administration can experiment with different use cases and share their experiences.

Finally, measure what you treasure. Policymakers can only know where to intervene if they know the state of AI adoption in Europe. Tracking AI adoption requires its own metrics to measure success and barriers, which are different from metrics for R&D in AI. We therefore recommend that the EU develops standard definitions of AI, its subcategories and the notion of 'adoption,' to be used across all its surveys and targets.

12 See eg Sanbox Vlaanderen: https://www.civtechalliance.org/sandbox-vlaanderen.

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