# The Adoption of Artificial Intelligence in Firms

New Evidence for Policymaking

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**Please cite this publication as:**
OECD/BCG/INSEAD (2025), *The Adoption of Artificial Intelligence in Firms: New Evidence for Policymaking*, OECD Publishing, Paris, https://doi.org/10.1787/f9ef33c3-en.

ISBN 978-92-64-80375-6 (print)
ISBN 978-92-64-57040-5 (PDF)
ISBN 978-92-64-35426-5 (HTML)

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# Foreword

This book is the result of a collaboration between the OECD, the Boston Consulting Group and INSEAD Business School. The OECD’s contribution has been implemented under the OECD programme on AI in Work, Innovation, Productivity and Skills (AI-WIPS), with the support of Germany.

The OECD’s input has been developed under the aegis of the Committee on Scientific and Technological Policy (CSTP). Many of the issues raised are relevant to CSTP’s upcoming work streams, especially in connection with the development, diffusion and governance of technology, innovation policies and the interface between research organisations and the business sector.

Work on AI in firms is one among a wide set of AI-related topics being examined by the OECD, overviews of which can be found at the OECD AI Policy Observatory.

# Acknowledgements

This study has been made possible thanks to support provided by Germany under the OECD Programme on AI in Work, Innovation, Productivity and Skills. The report is the fruit of a collaboration between the OECD, the Boston Consulting Group (BCG) and INSEAD Business School.

Alistair Nolan and Andrés Barreneche managed the study from the OECD Secretariat's side. From BCG, François Candelon, Rodolphe Charme di Carlo, Clement Dumas, Matthieu Gombeau, Lisa Krayer, Max Männig, Gigi Yang and David Zuluaga Martinez led and contributed in multiple ways to the project. BCG also provided funding to implement the enterprise survey.

Theodorus Evgeniou led the INSEAD Business School's contribution with support from John Fernald.

The literature review presented in Chapter 2 is based on a draft authored by Stephen Ezell and Viktor Lazar of the Information Technology and Innovation Foundation. They, in turn, were assisted by Robert Atkinson, Ian Clay, Dan Castro, Nigel Cory, Jessica Dine, Jaci McDole and Hodan Omaar. Chapter 3, which presents and analyses the Group of Seven (G7) survey data, is based on work by Daniel Erdsiek and Hildegunn Kyvik Nordås. Chapter 6 reports the results of the same survey administered in Brazil and is the result of work by Alexandre Barbosa, Thiago Meireles, Leonardo Melo, Marcelo Pitta, and Fabio Senne of the Brazilian Network Information Centre. Thanks are likewise due to the Fundação Sistema Estadual de Análise de Dados (Statewise System for Data Analysis Foundation) for its role in collecting and analysing the survey data.

Several independent experts provided guidance on survey design and methods, previous survey findings, and related aspects of policy. These include Catherine Aiken, Gerli Baldzens, Benoit Bergeret, William Clements, Irene Ek, Sam Hainsworth, Laurence Liew and Christian Rammer.

Thanks are also due to colleagues in the OECD Secretariat for guidance, analytic input and support in the publication process. These include Brigitte Acoca, Thyme Burdon, Alessandra Colecchia, Sylvain Fraccola, Beatrice Jeffries, Pierre Montagnier, Blandine Serve, Vincenzo Spezia, Stephan Vincent-Lancrin, and Kyriakos Vogiatzis. Thanks are further due to Tausif Bordoloi, who provided valuable research assistance during an internship at the OECD.

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# Executive summary

This study combines several types of data and information to explore the adoption of artificial intelligence (AI) in enterprises and how governments can support this. The core of the study is a policy-oriented survey of 840 enterprises implemented in the Group of Seven (G7) countries – the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises* - plus 167 enterprises in Brazil. The survey includes novel questions on topics such as enterprises' views on the value of public policies relevant to AI uptake, and their priorities for future AI policy. Other novel questions seek information on familiar topics, such as enterprises' use of cloud computing, but with new emphases – such as probing why cloud computing, an important adjunct to AI, might be underutilised. Complementing the survey, this book also contains studies of public sector institutions that help technology diffusion, along with interviews with enterprises.

Achieving higher rates of AI adoption could raise labour productivity and have other desirable outcomes, such as lower defect rates in production, reducing the need for material inputs. Policy insights from this and other comparable studies will likely become more important as more enterprises seek to become active users of AI.

It is widely reported that a scarcity of skills – particularly specialised talent – hinders AI uptake, even in many large firms. This study shows that policies and programmes to develop human capital are among the most valued and used by businesses. Many enterprises express a desire to better understand how to identify and use the right AI skills. However, academic certifications may not provide all the information employers seek. Updated qualification frameworks could help. Public sector providers should collaborate with industry to design relevant training materials, and training programmes should be tailored to industry or business-specific needs (such as using AI to optimise supply chain management). Training on real-world projects, using AI systems and datasets common in specific areas of business, is particularly valuable.

## Businesses want better quality public data and simplified means of access

Policy makers need to prioritise the quality of data in public repositories, for example by removing outdated or conflicting information. They should strive to simplify procedures for acquiring public data wherever possible. To aid users in understanding the data's meaning and context, comprehensive documentation should be made readily available. Furthermore, establishing centralised platforms for accessing public sector data could streamline search and retrieval processes. Policy makers should also seek to enhance the compatibility of legal frameworks governing cross-border data flows. International data sharing can pose severe challenges for companies that operate in multiple jurisdictions.

## Collaboration with universities and public research organisations is significant but could be enhanced

To help use and develop AI, enterprise collaborations with universities and public research institutions are widespread, highly valued and have several purposes. Some public financial support for collaborations, especially the first experience, could help to mitigate risks and reduce hesitancy among some firms.

Research and development (R&D) tax incentives can also be designed to encourage industry-university collaboration and research commercialisation.

The process of applying for public funds that aid collaborative AI research should be straightforward. Information could be made widely available describing funding opportunities, evaluation criteria and examples of successful applications. Firms and universities could benefit from the development of model framework agreements for collaboration. Additionally, universities and public research organisations should ensure transparency in their key operational practices, for instance, in terms of overall project governance.

## Dedicated public institutions can help the spread of AI in firms

Most OECD countries have public institutions dedicated to facilitating firms' uptake of digital technologies, including AI. These institutions frequently highlight uncertainty over the return on investment as a critical obstacle for firms considering adopting AI. They emphasise that a lack of data maturity is a fundamental barrier to implementing AI. Additionally, they report that managers often struggle to understand how AI can address real problems in the workplace and simultaneously underestimate the enterprise-wide implications and changes in business culture that AI may entail.

These institutions implement many types of initiative, from developing proofs-of-concept demonstrating how AI can help firms, to creating networking and collaborative platforms to help build AI ecosystems of public and private actors. A significant share of enterprises has used and positively values various public services to aid the adoption of AI. The diverse and sometimes innovative designs of these initiatives across institutions and countries offer opportunities for policy learning.

## An important step is to help firms find the right information and advice

Even though many of the sampled enterprises use AI in advanced ways, they still seek additional information on several domains of AI. This suggests that policy makers should look for cost-effective ways of signposting and/or providing easily findable, accessible, current, and specific information and advice, for instance, on regulatory updates, compliance guidance and evolving business use cases for AI.

Governments could also provide guidelines or a framework to help small and medium-sized enterprises navigate the vendor selection process, indicating, for instance, important considerations to be aware of when choosing an AI vendor. Guidelines outlining agency roles and expertise, along with mechanisms for companies to communicate their needs, would also help. Enterprises also wish to see clearly stated accountability frameworks for the safe use of AI. Policy makers need to examine regulations for ambiguities and assess how best to communicate regulatory information to firms.

## Improving the evidence base for AI policy

Better international comparability among surveys of AI in firms would help policy making. Several national statistical offices helped to shape the 2022-23 OECD/BCG/INSEAD survey questionnaire, and several of its new questions might be considered for inclusion in future national surveys.

Policy makers should examine the cost, scale and impact of diffusion institutions' work as well as related policies towards the uptake of AI. Most such institutions only work with a limited number of client firms. Key questions to address include whether these bodies generate wider demonstration effects and, if so, the magnitude of such secondary impacts. Such analyses would help in shaping efforts to diffuse AI more widely.

# 1 New evidence for policy making in artificial intelligence

This chapter reports the overall findings of the OECD/Boston Consulting Group/INSEAD study, conducted in 2022-23, that explored the adoption of artificial intelligence in firms and how governments can support this. Beyond an opening review of prior research, the core of the study is a novel policy-oriented survey of enterprises implemented in the G7 countries and Brazil. This is complemented by studies of public sector institutions that help the diffusion of technology as well as structured interviews with enterprises. This chapter also sets out the main policy implications.

## Introduction

Increasing the rate of growth of economic productivity is one of the greatest policy challenges facing OECD countries. OECD countries have experienced a decades-long period of stagnating productivity. Raising productivity is critical to raising living standards and enabling countries to cope with the consequences of rapid population ageing. Across the economy, artificial intelligence (AI) could be an important source of the needed productivity increases.

This study is the fruit of a partnership between the OECD, the Boston Consulting Group (BCG) and INSEAD Business School. It combines several types of data and information to explore AI adoption in firms and how governments can support this. Beyond an opening review of prior research, the core of the study is a novel policy-oriented survey of 840 enterprises across the Group of Seven (G7) countries plus 167 in Brazil. The survey in G7 countries was conducted between November 2022 and January 2023. The survey in Brazil was implemented between February and July 2023. Complementary insights came from structured interviews with leaders of 19 major public institutions from G7 countries and Singapore that work to accelerate the spread of digital and other technologies, including AI. These include organisations like Germany's Fraunhofer IAO/IPA, the United Kingdom's Digital Catapult and the United States' Manufacturing Extension Partnership programme.

A further element of the study is a synthesis of findings from in-depth interviews with managers in enterprises adopting AI. These experts hold positions such as chief information officer, chief technology officer, head of R&D, and chief technology officer, among others. The interviews serve to test the survey findings and further elaborate what the private sector most seeks from government.

The 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises* has several distinctive features. The first is a significant focus on policy. This entailed developing, testing and including novel survey questions on topics such as enterprises' views on the value of public policies relevant to AI uptake and their priorities for future policy. Other novel questions seek information on familiar topics, such as enterprises' use of cloud computing, but with new emphases – in this case, probing why cloud computing, an important adjunct to AI, might be underutilised.

A second distinctive feature of the survey is that it provides standardised data on AI in firms across G7 countries, plus Brazil. Other standardised supranational surveys focus only on countries in the European Union. While the survey covers a numerically small sample of enterprises and countries, G7 countries play an outsized role in AI globally. By one estimate, for example, France, Germany, and the United Kingdom alone account for around one-half of all AI talent in Europe (LinkedIn Economic Graph, 2019[1]). Similarly, among OECD countries, the United States is the dominant source of venture capital investment in AI-related early-stage firms (Tricot, 2021[2]).

An additional feature of the survey is its exploratory character. A longer-term goal is that some survey questions, or variants thereof, which all underwent cognitive testing, might be incorporated in subsequent surveys performed by national statistics offices (NSOs) or supranational bodies. Indeed, NSOs and other organisations with experience in the design and administration of large-scale surveys of AI in firms helped design the OECD/BCG/INSEAD questionnaire.

The book has six chapters. This opening chapter reports the key findings from all elements of the study. Chapter 2 provides an overview of previous survey-based research on AI in firms, focusing on the extent of adoption in the business sector and the barriers to uptake. Chapter 3 reports the findings of the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises*. Chapter 4 reports the results of structured interviews with public and public-private organisations that work to assist firms' use of digital technologies, including AI. Chapter 5 summarises the key policy-relevant insights from interviews with C-suite managers and technical experts in firms that have adopted AI. Finally, Chapter 6 presents the results of a survey of enterprises in Brazil using essentially the same OECD/BCG/INSEAD questionnaire.

The remainder of this chapter has several subsections. These are dedicated, sequentially, to the goals of the study; choice of enterprise size and sector; novel survey content; implementation and statistical features of the survey; a summary of previous research literature; a description and analysis of the survey findings; summaries of the main insights gleaned from structured interviews with diffusion institutions and senior staff in enterprises; and the key findings from the survey in Brazil. The chapter concludes with an overview of the principal policy insights from the entire study.

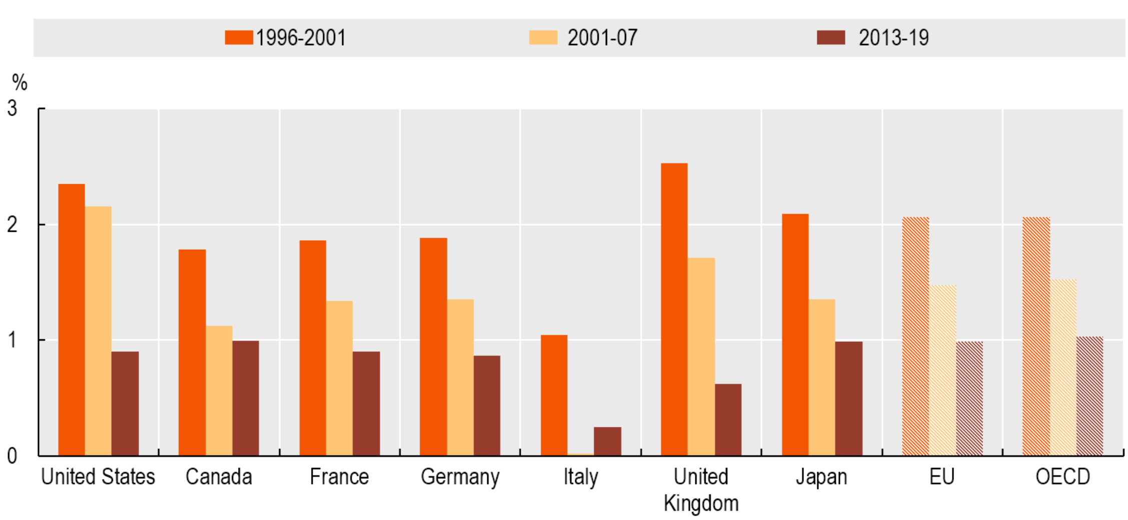
An important point to note is that the survey was developed and administered before the November 2022 release of ChatGPT. ChatGPT and successor large language and/or multimodal models (LLMs and LMMs) promise many uses in business, for instance, in programming, creating intuitive conversational interfaces, handling customer enquiries, generating maintenance manuals, integrating and transferring data and information from across a business when the former exist in otherwise incompatible formats, multi-lingual communication with suppliers, and so on.

The speed of adoption of LLMs and LMMs, their business impact, and the challenges involved in deploying are all pressing questions. This study's view on the state of AI adoption as of early to mid-2023 provides a critical perspective on what was already happening prior to the latest generative models. This is a strong starting point for researchers trying to ascertain the adoption trajectory of the latest family of AI technologies, especially insofar as their technical characteristics may change the factors that have aided or hindered AI adoption in the recent past.

## The rationale for this study

In recent decades, nearly all OECD countries have experienced a decline in the rate of growth of economic productivity, that is, the balance between the volume of economic inputs and outputs. Productivity growth is the main driver of rising incomes and living standards. Across OECD countries as a group, labour productivity growth in 2013-19 was only around half of that in 1996-2001 (Figure 1.1). New technologies, including AI, hold the promise of raising labour productivity (later sections of this chapter describe several examples of how).

### Figure 1.1. Average growth rates of GDP per hours worked in OECD countries, 1996-2001, 2001-07 and 2013-19




Note: To maintain consistency of the panel over time, Korea and Estonia are excluded from the OECD average (not available for all years in the first sub-period considered). The period 2008-13 is excluded as it is largely influenced by the Great Financial Crisis and the European debt crisis.
Source: OECD Productivity Database, https://www.oecd.org/en/publications/serials/oecd-productivity-statistics_g1g72f69.html.

Increasing productivity is both a short and long-term imperative. In the short term, the economic aftermath of the coronavirus (COVID-19) pandemic and the ongoing disruption of the war in Ukraine have increased the importance of productivity growth. Over the longer term, the productivity challenge could become more urgent still, owing to the economic and social consequences of demographic change. Old-age dependency ratios – the number of people older than 65 years per 100 persons of working age – are projected to at least double in most Group of Twenty (G20) countries by 2060. This means that those who are working will need to become more productive still, to offset the fact that they will be fewer in number (other things, especially immigration, unchanged). The problem will be made more acute because more young people may leave the workforce to care for ageing parents. In addition, more of society's resources will be dedicated to retirement-related transfers and healthcare. OECD countries will adapt, for instance, by raising the age of retirement. However, without improvements in labour productivity, which AI could help bring, these developments could cause severe economic stress.

A further reason why it matters to better understand AI adoption has to do with the labour market. In recent years, many studies have sought to estimate the effects of AI on labour demand. Many studies have suggested significant disruption as more cognitive tasks workers perform are substituted by AI. An early example of this work is (Frey and Osborne, 2017[3]), which examined the probability of computation of over 700 occupations, concluding that 47% of total US employment is attributable to occupations potentially automatable over one or two decades. Other studies have used other methods and arrived at different estimates. For instance, Arntz, Gregory and Zierahn (2016[4]) account for the distribution of automatable tasks within occupations and conclude that across 21 OECD countries, around 9% of jobs are automatable. (Lassébie and Quintini, 2022[5]). focus on the automatability of skills and abilities, which they then link to occupations. They find that, on average across OECD countries, occupations at highest risk of automation account for about 28% of jobs.

More recently, in research for the International Monetary Fund, (Cazzaniga et al., 2024[6]) add to studies using a purely task-based approach by also examining whether AI complements or replaces job roles. The authors conclude that almost 40% of global employment is exposed to AI, rising to around 60% of jobs in advanced economies, owing to the greater presence of cognitive-task-oriented jobs. However, a main point with respect to survey work, of which this report is a part, is that the results of such studies hinge on assumptions about the rate of adoption of AI and other forms of automation. The studies cited above are concerned with what is automatable in principle. However, as the literature review in Chapter 2 and the data in this study from Brazil show, adoption at the aggregate level has been relatively limited to date.

Data and information from this study could also help inform the ongoing development of practical guidelines for the implementation of the OECD Recommendation on Artificial Intelligence (the OECD AI Principles) (OECD, 2019[7]). This is particularly so for those recommendations that have to do with policies fostering AI-related innovation, entrepreneurship, and productivity growth in firms.

## Development and scope of the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises*

### *Avoiding duplication of existing survey evidence*

The starting point for deciding the content and scope of the current survey was to consider what prior national and supranational surveys already revealed about the diffusion of AI in firms. Over the past decade or so, several national and supranational institutions and other public and private organisations have conducted surveys to investigate the extent of AI uptake and some of its key characteristics. These surveys have different sample coverages and designs and yield different insights. However, as detailed in Chapter 2, several messages consistently emerge from this work, including that:

- The extent of diffusion of AI in the business sector is generally low but still varies considerably across countries.
- Small enterprises use AI much less frequently than larger enterprises**.**
- Certain sectors, such as financial services and information technology (IT) services, consistently register the highest shares of AI use in firms.

Accordingly, designing a survey to replicate such facts would be redundant. In addition, these findings are based on survey sample sizes beyond the financial resources available for the current exercise. The same goal of avoiding duplications informed the choice of questions about several common barriers to AI adoption, often broached in public and private-sector surveys as well as case studies. Chief among these standard questions is the availability of skills and the cost of adopting AI.

One upshot of the aim of avoiding duplication is that the survey includes AI users only (rather than seeking to assess the aggregate extent of AI use in the corporate sector). Furthermore, the survey only includes enterprises that classify themselves as active rather than passive users of AI, again a difference from many national surveys. It is hoped that understanding the policy needs of active users will provide useful insights into measures to assist other enterprises as they become or aim to become active AI users. Annex A compares selected features of recent national and supranational surveys of AI in firms with the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises*.

The survey sought and achieved completed responses from 840 AI-using enterprises across the G7 countries. Completed responses were sought from 120 enterprises in each country. In each country, the survey was addressed to enterprises in two size classes: medium-sized enterprises (between 50 and 249 employees) and larger enterprises (250 or more employees). The survey focused on enterprises in two sectors: manufacturing and information and communication technology (ICT). In addition, only two ICT sectors were considered: International Standard Industrial Classification of All Economic Activities (ISIC) 62: Computer programming, consultancy, and related activities and ISIC 63: Information service activities (activities relating to the manufacture of devices and components, such as semi-conductors, used in data and information processing and communication were not included under "ICT"). Table 1.1 shows the size and sectoral distribution of respondent enterprises per country. Only active users of AI were considered. The next section explains why these sectoral and enterprise size classes were chosen.

The survey has an exploratory character. Budgets permitting, it could eventually be implemented, with possible revisions, across a wider set of countries, sectors, and enterprises, while also using a sampling frame and probabilistic method allowing generalisation to national populations of enterprises. Doing so would strengthen cross-country and cross-firm statistical analyses.

### Table 1.1. Number of surveyed enterprises: Size and sectoral distribution per country

| | Medium-sized (50-249 employees) | Large (250+ employees) |
|---|---|---|
| Manufacturing | 30 enterprises | 30 enterprises |
| ICT | 30 enterprises | 30 enterprises |

### *Reasons for focusing on manufacturing and ICT*

Manufacturing is a priority sector for many OECD and non-OECD countries: national initiatives for advanced manufacturing have proliferated in recent years. Some examples are Germany's Industry 4.0 programme, the National Network for Manufacturing Innovation in the United States, Japan's Robot Strategy, and the People's Republic of China's Made in China 2025 and Internet Plus initiatives. Indeed, over 30 countries have developed national programmes for Industry 4.0, while many more have prepared manufacturing foresight studies and strategies, as well as in-depth roadmaps for manufacturing technologies deemed strategic. Manufacturing has also grown as an area of emphasis in recent national research and innovation strategies.

In addition, there are many uses of AI in manufacturing, and the potential for new applications is large. Early forms of AI – known as expert systems – have, in fact, been a part of manufacturing for over 40 years. However, their use was limited to just a few applications, such as process scheduling. Newer types of AI, which learn and make predictions from data, now have a role in many business processes, including:

- **Industrial research**: A compelling example comes from Boeing, which wished to mass-produce 3D-printed metal parts for jets. However, most useful metal alloys are not printable because the different powder grains do not stack well. Boeing turned to an AI system belonging to Citrine Informatics. The AI trawled through decades of experiments, scanning 10 million possible recipes for alloy powders. Citrine Informatics wrote software so the AI could even scan data from old reference books and handwritten notebooks. The process of discovery of materials, which usually takes years, was shortened to days (WIRED Chen, 2017[8]).
- **Product design**: AI-driven design software, combined with 3D printing, is revolutionising industrial design. Such software can generate vast numbers of potential designs, selecting those best suited to requirements. A novel aircraft bulwark partition was developed and incorporated using such a system in Airbus' A320 aircraft. The new partition was stronger than the one it replaced and 45% lighter (Airbus, 2016[9]).
- **Fabrication and assembly**: Another important use of AI is in quality control. In the semi-conductor industry, for example, defects in computer chips can appear as irregular shapes on otherwise regular circuit patterns. The irregular shapes attract feature detectors driven by AI.
- **Process control**: "Digital twins" are computer models of a machine, or system of machines, based on real-time data from sensors in machinery. Aided by AI, the computer models help to monitor production, optimise key parameters and predict maintenance needs.
- **Supply chain management**: BMW (Bayerische Motoren Werke AG) has set a goal of knowing the real-time status of all major production equipment at each company producing key components for its vehicles. Information of this sort can extend upstream to the supply of production inputs and downstream to distribution and retail. AI can help integrate and improve supply chains, for instance, by predicting fluctuations in customer demand and efficiently scheduling distribution.
- **Training and cognitive support**: In aerospace, when building its A350 aircraft, Airbus deployed AI to analyse process disruptions. If a worker encounters an unfamiliar problem, the AI can suggest solutions by analysing a mass of contextual data on similar problems from other shifts or processes. The AI cut time lost to disruptions by a third (Ransbotham et al., 2017[10]). AI is also enhancing workforce training (using virtual reality) and cognitive assistance (using augmented reality). For example, a technician might see suggested solutions to production problems projected on a safety visor.

AI can also support generic business functions that matter to manufacturers and firms in other sectors. An example is digital security. Digital security incidents appear to be increasing in sophistication, frequency and impact and intensified during the COVID-19 pandemic (OECD, 2020[11]). In one incident, hackers broke into the computers of a German steel mill and overrode the shut-off mechanisms on the steel mill's blast furnace. Among other advances, AI systems can recognise when text is likely part of a password, helping to avoid accidental online dissemination of passwords. As occurs in many sectors, AI in manufacturing can also be applied in customer-facing processes such as business-to-business (B2B) marketing and pricing.

Unlike sectors such as insurance and finance, which for many years have led in using big data, manufacturing has traditionally been product-led, with a less prevalent culture of and familiarity with data analytics. However, manufacturing is one of the most data-intensive parts of the economy. As the understanding of how to create value from industrial data grows and as AI and data analytics practices spread within manufacturing, productivity gains could be significant (Atkinson and Ezell, 2019[12]). The automotive sector is an example of where AI in manufacturing is becoming transformative (Box 1.1).

### Box 1.1. AI in the automotive industry

AI is fundamentally changing the automotive industry, both in production and in the vehicles themselves. In production, among other applications, AI is helping manufacturers significantly reduce the time needed for design approval and authorisation. Combined with the Internet of Things (IoT), AI enables predictive maintenance and transforms quality control. For instance, with the help of computer vision and machine learning, manufacturers can detect even minor imperfections in vehicle components. Globally, the automotive sector has led advances in industrial robotics. AI is helping make such robots more autonomous, for instance, in efficiently and accurately picking parts. In a particularly advanced application, AI-enhanced robots have been used to co-ordinate workflows in combined human-machine teams.

AI is also revolutionising automotive logistics. By ensuring the right parts are available at the right locations and times, companies can minimise inventory holding costs and reduce the need for expedited shipments. As a result, some automotive companies have achieved up to a 30% reduction in logistics-related costs. AI is also used to identify when customers might be willing to purchase an upgraded product or service or related products or services.

Vehicles themselves are evolving due to AI. Using cutting-edge AI algorithms, vehicles can analyse extensive sensor data – from cameras, lidar and radar – to perceive their surroundings and make smart decisions. Over 80 companies in the United States alone are currently testing self-driving cars. Cars are also becoming software platforms, facilitated by AI. Many automakers deliver over-the-air software updates to vehicles, and some cars transmit enormous volumes of data back to manufacturers. AI-based car occupant monitoring systems are set to increase passenger safety, for instance, by monitoring the interiors of cars and ensuring driver attentiveness. AI-powered security systems, such as lane departure warning and autonomous emergency braking, are already enhancing safety, while seamless communication between cars will help maintain safe distances on the road. In addition, AI will affect automotive insurance, for instance, by gathering incident data to complete claim forms.

The industry faces several challenges related to data, technical limitations and regulation. For example, obtaining sufficient clean data on rare events is a problem. By facilitating large-scale data collection, connected fleets will help address this limitation, but other approaches are also needed. As AI systems require access to sensitive vehicle and user data, manufacturers must also employ secure data-handling practices, including encryption and access control, to safeguard data during transmission, storage and processing.

Source: Based on analysis from Eugene Hayden, Boston Consulting Group, drawing on Appinventiv, “AI in the automotive industry”, https://appinventiv.com/blog/ai-in-automotive-industry/; Boston Consulting Group, “Auto.AI research”, http://www.bcg.com/beyond-consulting/bcg-gamma/auto-ai; TaskUs, “Future trends in autonomous vehicles”, http://www.taskus.com/insights/future-trends-autonomous-vehicles/.

Compared with many other parts of the business sector, enterprises in ICT are major users and developers of AI, especially enterprises in the ICT subsectors examined in this survey (to recall, these are: ISIC 62: Computer programming, consultancy, and related activities; and ISIC 63: Information service activities). Table 1.2. shows data on the share of enterprises that use AI in manufacturing and ICT drawn from four national surveys. Precise comparison across countries is hindered because the included areas of economic activity do not overlap perfectly (the Swedish survey included a wide range of publishing activities). Nevertheless, in all the surveys the share of AI-using enterprises in ICT is far higher than in manufacturing; in Canada it is more than ten times higher.

### Table 1.2. Share of firms in manufacturing and ICT that use AI (selected national surveys umber of survey)

| Country | Manufacturing | ICT | Source |
|---|---|---|---|
| Canada | 1.9% | 20.4% | Statistics Canada (2017) |
| Germany | 2.2-11.0% (depending on the subsector) | 18.3% | ZEW (Rammer, Fernández and Czarnitzki, 2022[13]). |
| Germany | 9.0% | 33% | Destatis (Destatis, 2023[14]) |
| Sweden | 3.5% | 22.7% | Statistics Sweden (2024) (data from 2019) |

Note: Sectoral classification for Canada: Manufacturing = NAICS 2017 31-33; ICT = NAICS 2017 541512
Sectoral classification for Sweden: Manufacturing = SNI_2007: 10-33; ICT = SNI_2007: 58-63
Sectoral classification for Germany: Manufacturing = NACE_Rev2: 10-12, 14-15, 31-32, 13, 16-18, 22-23, 20-21, 24-30, 33; ICT = NACE_Rev2: 61-63.
Source: Rammer, C., D. Czarnitzki, and G.P. Fernández, "Artificial Intelligence and Industrial Innovation: Evidence from Firm-Level Data (2021)", https://ssrn.com/abstract=3829822; Destatis, "IKT-Indikatoren für Unternehmen: Deutschland, Jahre, Wirtschaftszweige (ICT indicators for companies: Germany, years, economic sectors)", https://www-genesis.destatis.de/datenbank/online/statistics, accessed on 3 June 2024.

Enterprises in ICT also use AI in a wide range of applications. This is particularly so for businesses in software development and programming, as well as those in data processing, hosting and online platforms. Such enterprises often use AI in the same generic business functions that a manufacturer might. Other uses can include:

- **Process automation**: AI is simplifying the work of programmers. AI tools can write working code, build on billions of lines of public code, learn to arrange code fragments and aid code completion. Some AI tools provide programmers with feedback as they type, suggesting alternative code that programmers can edit as they please. AI can also learn from and adapt to programmers' coding habits and preferences.
- **Quality control**: AI helps software developers test code and identify defects more efficiently and quickly than human inspection alone. AI can also process data on how software is used across devices, users in different population groups, and locations.
- **Social media analysis**: AI can gather and process large volumes of data from social media and use the results to help predict market demand and customer behaviour.
- **After-sales services**: Service desks can be highly automated. For example, AI can draw on historical data from across a company to help provide users with solutions to problems. An AI might interpret a user's service-related questions, seek similar service questions and answers from company records, and propose response options most likely to be correct. Overall, service management can be made faster, cheaper and more effective.

With the above considerations in mind, Annex B shows the business sectors targeted by the survey. Because countries use different classificatory systems, Annex B also maps the codes from the ISIC to the national classification systems used in individual G7 countries and Brazil.

#### *Reasons for focusing on medium-sized and large enterprises*

The survey targeted enterprises in two size classes: medium-sized enterprises (50-249 employees) and large enterprises (250 or more employees). Small enterprises (with 0-49 employees) were not sampled. Analytic and budgetary reasons motivated the choice of targeted size classes.

As described in Chapter 2, in all OECD countries, AI use rates are very low in core business processes in small enterprises (i.e. with fewer than 50 employees). This raises the administrative cost of a survey aimed at small enterprises that are AI users. Moreover, it was judged that for several reasons, less policy analytic value might come from focusing on small enterprises. In addition to AI being much less prevalent than in larger enterprises, smaller enterprises tend to use AI in less sophisticated ways. Moreover, the reasons for their non- or limited use of AI are relatively well understood and often stem from inherent problems of scale, irrespective of technology. For instance, smaller firms tend to be more financially constrained when considering investment in AI. However, it is a common feature of small enterprises that many of the investment decisions they face – not just with respect to AI – involve financial challenges coming from, for instance, the difficulties of managing cash flow when product lines are few. Similarly, on account of scale, smaller enterprises generally have a more limited internal division of labour, meaning that functional specialisations such as research and development (R&D) are less developed. Consequently, an alternative focus on medium-sized and large enterprises, which are more likely to have adopted AI in core business processes, and in more far-reaching ways, could provide richer insights for policy makers regarding the adoption process. Such insights would become more relevant over time as today's numerically larger group of small firms seek to adopt AI.

A reason for including medium-sized enterprises in the sample, rather than focusing exclusively on large enterprises, is that they are often a target of government policy to accelerate the diffusion of new technology. Tracking over 700 national AI policy initiatives from 60 countries, the OECD AI Observatory shows that around 15% of AI-related policies specifically target small and medium-sized enterprises (SMEs) (with some 4% aiming at large firms) (OECD, 2024[15]). It is unclear how many of those initiatives balance towards smaller enterprises, but supporting medium-sized enterprises is clearly a goal. In addition, a reason for focusing on medium-sized manufacturers is the possibility that in the relatively recent process of developing national AI strategies, the specific needs of this group of enterprises may have received insufficient attention (Bergeret, 2020[16]).

With respect to the classification of enterprises as medium-sized, the definition used in the European Union relies on two variables: the enterprise should employ between 50 and 249 persons and have an annual turnover not exceeding EUR 50 million and/or an annual balance sheet total not exceeding EUR 43 million. The OECD also uses the EU definition. However, the definition of an SME used by national authorities differs across non-European countries. In Japan, a country included in this survey, an enterprise is considered an SME if it employs from 4 to 299 employees. In the United States, SMEs include firms with fewer than 500 employees. Nevertheless, selection criteria based on enterprise turnover were not used in the OECD/BCG/INSEAD survey, as requests for such information could dissuade some potential respondents from participating (by contrast, surveys that request financial information often entail a legal obligation to respond when conducted by NSOs).

### *Novel content in the 2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises and areas of overlap with prior surveys*

The choice of topics covered in the survey reflects extensive consultation with independent experts, NSOs and delegates in OECD policy committees and working groups. As noted earlier, the aim is not to gauge the overall incidence of AI use in enterprises in G7 economies but to explore the policy and institutional conditions that affect the application and development of AI.

Annex C contains the full survey questionnaire. The questionnaire begins with a series of screening questions. These establish the enterprise's location, size, and sector, as well as whether it uses AI, whether the use of AI is active or passive, and how AI is applied. Enterprises that meet the screening criteria then proceed to 19 questions, each with multiple response options. These 19 questions examine the following topics:

- **How important is AI to the enterprise**: A question gauges if AI is critical to the enterprise, one among several important considerations, or of minor importance.

- **Data infrastructures**: Questions explore sources of data acquisition for AI, enterprise-level data maturity, the types of professional roles in the enterprise relevant to data and information processing, the number of employees working in those roles, and the reasons for limited or non-use of cloud computing.
- **Building AI capabilities**: Questions examine practices used to adopt AI, including partnerships with universities and public research organisations, the use of public services to help adopt AI, obstacles experienced in adopting AI, recent experience recruiting graduates, and understanding of required skill sets.
- **National policies and regulation**: Questions consider the usefulness that enterprises accord to different public measures to strengthen staff skills, the usefulness for adopting AI of different public policies and support services, and awareness of and views on the utility of various types of regulation.
- **Research and innovation**: A question examines the share of the enterprise's R&D related to AI and whether the enterprise invests in R&D at all.

Relative to prior cross-country work, as well as most national surveys, the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises* asks novel – or infrequently put – questions, including on the following subjects:

- AI applications by the business function they are used for, while in much of the wider literature, AI applications are typically characterised by technology. Examples of business functions are product design, human resources, and R&D. Examples of AI technologies are speech recognition, image recognition and natural language generation. Each AI technology can be used in many functions. For instance, natural language processing can be used in staff recruitment and human resource management, training and cognitive support for workers, customer-facing services and other functions. Thus, enterprises may exploit economies of scope associated with AI technologies, using them in several business functions once they are introduced.
- Not just the roles of skills as a barrier to adoption but the less frequently addressed question of whether enterprises fully understand skills needs and if formal academic qualifications fully and clearly align with job requirements.
- The incidence of use of different types of public services useful to adopting AI.
- Enterprises' preferences and needs concerning the types of services provided by the wide range of public programmes in all OECD countries to accelerate the diffusion of technology in firms (see Chapter 4).
- The use of, and types of, collaboration with students and faculty in tertiary education institutions and partnerships with public research organisations.
- Enterprises' prioritisation of public policies in areas ranging from data to the regulatory environment.
- The reasons for non- or limited use of cloud computing (rather than the frequently surveyed use of cloud computing).
- Firms' allocation of their R&D spending to AI.

The survey also includes questions on topics explored in prior firm-level surveys. Such questions cover essential characteristics of enterprises' use of AI and the challenges faced in developing AI applications.

### *Implementation and statistical features of the 2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*

The available budget determined the survey's sample size and sampling process. During implementation – between November 2022 and January 2023 – the survey respondents were identified as AI-using enterprises from a pool of enterprises with a high probability of being AI users (drawing on a roster held by a survey administration company). The survey consists of 840 AI-using enterprises, a significantly higher number of observations than most studies focusing on AI-using enterprises.

However, with 120 observations per country and using a sampling approach that relied on a survey provider database with non-representative statistical characteristics and a search procedure selecting AI users, the findings and the underlying sample are not representative of the population of enterprises in each country. In other words, the results relate to averages among the surveyed enterprises and are not directly generalisable to the respective population of enterprises within a given country. However, the survey in Brazil, reported in Chapter 6, used essentially the same questionnaire but was conducted using a probabilistic sampling procedure, yielding results statistically representative of 2 561 enterprises in the State of São Paolo. A fuller discussion of how the survey was implemented and the statistical character of the results is given in Annex D.

## Key findings

### *According to the literature, business uptake of AI applications is still relatively low and mainly occurs in larger firms and in the ICT, finance, and insurance sectors*

Chapter 2 discusses the findings of prior survey-based research on the diffusion of AI in firms. The focus is on AI in manufacturing and in ICT services, the same sectors covered by the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises*.

The prior literature shows that AI adoption is generally the exception across firms, with single-digit adoption rates being common in several sectors in many countries. For example, a major 2020 study in the United States across all AI-related technologies and all firm types found that the overall adoption rate was just 6.6% (Zolas et al., 2020[17]). In the European Union, a 2023 study showed Denmark and Finland have the highest share of enterprises utilising at least one AI technology, both at around 15%. The European Union average was 8%. Italy and France had shares of 5% and 6%, respectively (Eurostat, 2023[18]). A separate study in 2019, covering all firms in Germany, found that only 5.8% used AI (Rammer, Fernández and Czarnitzki, 2022[13]). In Brazil, a 2021 survey showed that 13% of companies use some type of AI (Brazilian Network Information Center, Brazilian Internet Steering Committee, 2022[19]).

Most surveys reveal a strong positive correlation between firm size and AI adoption. For instance, a 2022 study in the United Kingdom found that 15% of small firms were adopting AI, compared to 34% of medium-sized firms (Evans and Heimann, 2022[20]). Only 2% of small firms, 5% of medium-sized firms, and 9% of large firms were piloting AI. The same study showed that larger firms that adopt AI are also more likely to adopt multiple AI technologies. In Japan, in a survey from 2021, the rate of use of AI in firms in the 100-299 employee size class was half that of firms with 1 000 to 1 999 employees (10% and 22% respectively) (MIC, 2021[21]). Similarly, the incidence of AI adoption in firms with 1 000 to 1 999 employees was less than half that of firms with 2 000 or more employees (at 22% and 48%, respectively).

Numerous factors could explain why large firms generally lead in adopting AI. For instance, large firms often serve larger markets, which allows them to spread the fixed costs of using AI in production over more sales, thereby lowering unit production costs. Similarly, large firms often offer superior workplace conditions, making attracting and retaining talent easier. However, even in large firms, adoption can be surprisingly limited. For example, Chapter 2 describes a 2019 survey of 60 manufacturers in the United States with annual sales of between USD 500 million and USD 10 billion. Over half indicated they were only at the initial stages of manufacturing digitalisation. At the time, just 5% of the companies had mapped where AI opportunities exist and developed a clear strategy for sourcing the data that AI requires. Furthermore, 56% had no plans to do so (Atkinson and Ezell, 2019[12]).

Most surveys concur that AI is more prevalent in some sectors than others, with the highest uptake rates generally being in ICT, finance and insurance, legal, and other professional and technical services (such as engineering, advertising, design and consulting).

While the existing literature shows use to be low overall, the figures on adoption rates cited above, and elsewhere in Chapter 2, vary considerably across countries. This points to a need to better understand the comparability of surveys across countries, as different methodologies may lead to discrepancies. Potential sources of discrepancy include the units of observation used (e.g. enterprises or establishments), survey sample sizes, choice of industries examined, and the size of sampled firms. Another source of variation could come from differences in the questionnaires themselves, such as how AI is defined, as well as differences in the wording and scope of the questions asked (Montagnier P. and Ek I., 2021[22]).

Chapter 2 also discusses why the adoption of AI is often limited. Repeatedly identified obstacles include a lack of digital and data readiness (including interoperability between equipment, which affects the data integration necessary for AI applications), the challenge of creating new business models, the cost of implementing AI, uncertainty about how to use AI solutions to solve specific challenges, uncertainty over the returns on investment (ROI) in AI, how to implement effective change management strategies, and lack of access to suitable and specialised vendors of AI solutions.

Acquiring or developing a skilled workforce is a common problem. About 85% of firms responding to an EU-wide survey indicated that hiring new staff with the right skills was the principal barrier to AI adoption (Kazakova et al., 2020[23]). Even among a sample of large US manufacturers with ample recruitment budgets, 47% lacked the skills necessary to implement AI technologies (Atkinson and Ezell, 2019[12]). These issues are discussed in greater detail later in this chapter and in Chapters 3 and 4.

## *The OECD/BCG/INSEAD survey covers enterprises that actively use AI and reveals the main characteristics of their AI adoption patterns, the challenges they face and their assessments of the role of public support*

### *Data maturity*

The surveyed enterprises were relatively data mature. Most – 78% – used at least one data management solution. Smaller enterprises were a little less likely than others to use a data management solution. In addition to data generated internally, between 51% and 61% of enterprises used external data, whether from private data providers (such as organisations dedicated to producing and selling data), a partner enterprise, or the public sector.

Before adopting AI, firms often need to implement digital technologies that systematically gather data, whether from business processes or interactions with customers and suppliers. High-quality and sufficiently voluminous data are essential to create, test, evaluate and validate AI models. As discussed in Chapter 4, agencies like Canada's Vector Institute, France's Cap Digital, Japan's New Energy and Industrial Technology Development Organization, and others can support the uptake of AI in business. Box 1.2 reflects the views of such organisations on how enterprises gather and manage data and how this affects the adoption of AI.

### Box 1.2. AI and data maturity in firms, the view from diffusion institutions

In their day-to-day work, diffusion institutions develop a deep familiarity with how the characteristics and behaviours of firms affect their attempts to adopt AI. A recurrent problem that diffusion institutions note is that many firms often do not possess data with sufficient quantity, quality, cleanness and structure. They frequently lack an adequate understanding of what information needs to be gathered systematically. Consequently, they may not have the necessary data collection mechanisms in place, or if they do, they struggle to assess how appropriate their data are for a given AI use case.

In addition to collecting the necessary data, firms face data management challenges. They often have to integrate data from different sources, such as software, machines, business areas within the firm, and data provided by third parties. Data sources can vary in periodicity (e.g. weekly, daily, hourly), type (e.g. quantitative or qualitative) and format (e.g. Excel spreadsheets, MySQL databases). Data can be unstructured, unlabelled and disorganised, making it challenging to integrate. Time and expertise are required to prepare data to build an AI model.

Data transfer and exchange also raise challenges. For instance, for fear of losing the value of the data they collect, companies are sometimes unwilling to sell it or to enter collaborative projects that exploit it. Data security (i.e. avoiding data breaches) and regulatory compliance are further concerns. Some enterprises are reticent to publish data or other results from work with diffusion institutions or from publicly funded applied research. This aversion can make partnering with research institutions difficult, as academics often want to publish their research.

Source: OECD/BCG/INSEAD interviews with senior staff from technology diffusion institutions.

#### *The most frequent and infrequent uses of AI*

Among the uses of AI examined in the survey, AI for R&D was the most likely and consistently used application across enterprises in any given industry and across industries overall. AI was least likely to be used in human resources management. The low frequency of use in human resource functions is perhaps unsurprising, as many enterprises have concerns about inadvertent misapplication of AI in recruitment, a possibility often raised in public discussion of AI.

#### *How enterprises adopt AI*

Enterprises were asked about the practices they use to adopt and develop AI. Most use several mechanisms. More than 70% of enterprises in both manufacturing and ICT report that they carry out R&D on AI technologies for their own use. Nearly three-quarters of enterprises in both sectors rely on employee training. Large enterprises in ICT are the most likely to train employees and hire staff to develop AI. In addition, more than 60% of the sampled enterprises hire new staff to help develop AI technologies. Between 53% and 64% of enterprises use customised systems built by third parties or purchase off-the-shelf software or hardware. About every second enterprise has institutionalised AI development by creating a senior management role or a team with responsibilities for AI. Establishing such senior functions and responsibilities can help promote understanding of AI across a business and help to implement some of the systemic changes that adopting AI can require (Box 1.3). Finally, many enterprises speed up the uptake of AI through partnerships with national or international enterprises that have AI capabilities.

### Box 1.3. Management and the adoption of AI across a business

As described in Chapter 4, even when firms have some familiarity with AI, managers often do not have a sufficient grasp of what AI is, what adoption entails, or what their businesses can gain from it. Many managers have a plug-and-play conception of adoption, expecting AI to be a commodity technology they can easily integrate into core business processes.

Compared to adopting other digital technologies, adopting AI can require a significantly larger company-level transformation involving changes to business operations across various departments. If managers lack AI literacy, they may fail to foresee or be unprepared to make the shifts in organisational structure, business processes and culture needed to adopt AI solutions. Many companies also run AI pilots without a strong vision or business plan to expand and integrate them more widely.

In addition, companies often fail to understand the extent of continuing investments required for AI quality management. Keeping AI models performing well over time requires constant assessment, retraining (with the most recent data) and redeployment.

Source: OECD/BCG/INSEAD interviews with enterprises.

In the survey sample, and perhaps unsurprisingly, spending on R&D for AI as a share of all R&D spending was positively related to how critical enterprises deem AI to be. 38% of enterprises that allocate between 0-10% of their R&D spending to AI considered AI to be critically important to their core business processes. By comparison, among enterprises that spend more than 30% of their R&D on AI, 87% considered AI critical to the business.

#### *Collaboration with universities and public research organisations*

Many enterprises in the sample collaborate with universities, public research organisations and other partners to support the use and development of AI. More than half have worked with university faculty, PhD, or postdoctoral students over the past 12 months. Roughly one-third work with undergraduate students.

Perhaps unsurprisingly, enterprises that spend more of their R&D on AI are also more likely to establish collaborations on AI with researchers in public research organisations. Between 60% and 65% of enterprises that spend more than 11% of their R&D on AI have such collaborations, compared to 44% of enterprises that spend less than 10%. The importance of R&D in connection with AI is noteworthy for policy makers, who possess various tools for encouraging and directing this form of investment. Educational and research institutions also possess a range of tools to facilitate R&D and related collaborations.

Enterprises often partner with universities to gain access to skilled graduates. A significant portion (76%) of enterprises involved in such collaborations had hired AI graduates within the past year. A further indication of the importance of AI skills is the share of enterprises that consider government investment in university education and vocational training related to AI to be “very helpful” or “helpful”. Even among businesses that do not prioritise AI in their core operations, 73% view such public investments as either "very helpful" or "helpful". Collaborations with researchers in public research organisations are particularly widespread among smaller manufacturers (64%).

## *Obstacles to using and adopting AI*

### Workforce skills

Identifying and implementing AI applications requires a mix of technical and domain expertise, generally involving employees with MSc or PhD diplomas. In addition, the presence of AI-skilled staff is often a prerequisite for venture capital funds to invest in firms developing AI applications. Access to AI talent can be very problematic, especially for SMEs. Smaller firms compete with large companies for limited AI specialists and data engineers with postgraduate education. Competitors for talent include tech giants such as Amazon, Google and Microsoft, which can offer more attractive salaries and work conditions. SMEs may also have more limited access to on-the-job training opportunities to help staff to build AI skills. In addition, countries often compete for talent at the postgraduate level, for instance, by offering higher PhD salaries.

The 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises* reiterates these findings and observations. Around 20% of enterprises with 50-250 employees report being unable to find appropriately qualified candidates for available vacancies. Even many large enterprises – approximately 17% – experience the same problem. In a context where AI skills are scarce almost everywhere, enterprises collaborate with universities to secure access to talented graduates. Indeed, a high share (76%) of enterprises collaborating with universities recruited graduates in AI in the previous 12 months.

### Many enterprises do not understand which skills they need

An under-examined question is whether firms fully understand their AI skills needs and whether formal academic qualifications provide sufficient information to employers making recruitment decisions. The survey asked if enterprises had experienced difficulties during the preceding 12 months in understanding the skills to look for in potential AI recruits. Almost 19% of respondents acknowledged having this problem. Indeed, 86% of enterprises that place a high value on public support for partnerships with educational and vocational institutions also consider the development of new qualification frameworks to be either “very useful” or “moderately useful”. All told, many enterprises in search of increased AI skills feel they need a better practical understanding of how to identify and use the skills in question. Updated qualification frameworks could help recruiters better assess how different AI skills can be applied in specific corporate contexts.

### Other obstacles to using AI

Respondents were asked to indicate which conditions, if any, had limited their enterprise in using AI over the preceding year. The most frequently experienced obstacle was the difficulty in estimating *a priori* the ROI in AI applications. Some 62% of manufacturers and 56% of enterprises in ICT cite this as problematic. This result echoes the experience of agencies across the G7 countries charged with accelerating the spread of digital and other technologies in firms (Box 1.4 and Chapter 4).

### Box 1.4. The challenge of estimating the ROI in AI

AI projects involve a degree of experimentation where the ROI is inherently uncertain. This happens even for well-established use cases. Interviews with diffusion institutions indicate that many firms – particularly SMEs – are uncertain about what they can gain financially from implementing AI. They may find it challenging to define and delimit the business case for adoption. Finding reliable estimates of the ROI can be difficult, even when applications are narrowly defined. For example, an AI system might be able to notify users about potential machinery failures, allowing a firm to conduct preventive maintenance on equipment. However, verifying the necessity of this intervention and confirming that it, in fact, prevented a breakdown (and its associated expenses) might not be straightforward. Having a documented history of breakdowns could assist in calculating the ROI for implementing such an AI system, but such data might not be easily accessible. In addition, the process of gathering reliable data incurs expenses that must also be considered in the ROI assessment.

While estimating an AI system's contribution to cost savings and efficiency gains can sometimes be relatively uncomplicated, calculating the ROI for new AI-enabled products, services, or business models can be more challenging. Service providers selling AI solutions also face ROI-related problems, as the right revenue model can be unclear (e.g. subscription, licence or charging per task, as some cloud computing companies do).

Source: OECD/BCG/INSEAD interviews with enterprises.

Over 40% of manufacturing and ICT enterprises reported difficulty finding AI system vendors that provide customised solutions. This issue has prompted some public sector agencies – such as AI Singapore – to adopt a process for recommending vendors with proven track records, with the goal of reducing search costs, particularly for small businesses (see Chapter 4).

Approximately 40% of enterprises lack clarity around the possible legal consequences of damages caused by AI, as well as a scarcity of cloud computing solutions that guarantee data security and regulatory compliance (see the following section on cloud computing). About 40% of businesses state that insufficient external funding for investment hindered their use of AI in the previous year. However, as might be expected, this result is sensitive to enterprise size: larger enterprises are considerably less likely to report such financial barriers (33% in manufacturing and 30% in ICT).

Roughly every second enterprise reports difficulties in retraining or upskilling staff, a finding which might be amenable to change through education and training policies. A further challenge is the apparent reluctance of some staff to retrain or upskill, as cited by 45% of manufacturers and 34% of enterprises in ICT.

Manufacturers experience almost all obstacles to AI adoption more frequently than enterprises in ICT. This might have several causes. For instance, manufacturing has historically been product rather than data-led and has less of a tradition of working with big data (although differences exist within the manufacturing sector, especially regarding continuous flow manufacturing, for instance, of petrochemicals, and manufacturing of discrete products, such as cars).

### Obstacles to using cloud computing

Prior research on AI adoption has revealed a pattern where organisations that are early adopters of websites and computer systems tend to be early adopters of cloud services as well, with AI adoption following suit. Survey participants were asked to specify the obstacles they encountered, if any, in using cloud services. The cost of retooling systems was the most frequently cited obstacle, both in manufacturing (60%) and ICT (56%). Approximately every second enterprise in both sectors had concerns about customisation of applications, corporate compliance or network stability. Roughly one-third reported that a lack of IT skills – for instance, in cloud engineering – limits their use of cloud computing. Finally, and somewhat surprisingly, a substantial share of enterprises in manufacturing (34%) state that they do not see advantages in cloud computing.

### *Public services to support the adoption of AI*

A main feature of the survey is its assessment of the extent to which enterprises use and value public sector services to support the adoption of AI. A key finding is that a significant share of enterprises use such services. The most frequently used services in ICT and manufacturing are those providing access to information or advice (75% in manufacturing, 69% in ICT). Initiatives to develop human capital are also among the most widely used and highly valued. Roughly 58% of enterprises make use of training services in some way supported by the public sector. In addition, 42% use public programmes that promote access to finance, such as tax credits on R&D spending, grants or credit guarantees.

Public sector services are most used by manufacturers with 50-250 employees. Some 85% of such enterprises use some form of information or advisory service, compared with roughly 68% for other groups of enterprises.

Enterprises in the United States are much less likely to use public sector services than enterprises in other countries. For instance, only 19% of the surveyed enterprises in the United States use services promoting access to finance, compared to 50% of enterprises in Japan.

#### Supporting growth in workforce skills in AI

Firms can increase the skills of their workforce in a variety of ways. Enterprises were asked about the usefulness of three types of support to increase staff skills in AI: partnerships with educational and vocational institutions; tax allowances or tax credits for training in AI; and support to develop qualification frameworks for graduates in the field of AI. Regardless of size, most enterprises indicate that one or more of these forms of public support would help strengthen staff skills in AI. Some 84% of enterprises indicate that partnerships with educational and vocational institutions would be either “very useful” or “moderately useful”. In addition, 67% of enterprises indicate that tax allowances or tax credits for training in AI would be “very useful” or “moderately useful”. As noted earlier in this section, most enterprises state that they would value support to develop qualification frameworks for graduates in the field of AI.

Across the survey sample, just over 50% of enterprises use AI to facilitate training or to provide cognitive support for workers. Applying AI for cognitive support is a relatively advanced use of the technology. Such applications frequently combine AI with other technologies, such as augmented and virtual reality.

#### Information services provided by the public sector to assist in the adoption of AI

A large majority of enterprises judge that information services provided by the public sector would be “helpful” or even “very helpful” to their use of AI. For any of the services considered, no less than 76% of enterprises indicate they would be at least “helpful”. Fully 83% of enterprises judged that having more information on current or forthcoming regulations around data or AI or on expected ROIs in AI would be either “helpful” or “very helpful”. It is striking that even though many of the sampled enterprises use AI in quite advanced ways, they still seek additional information on various domains of AI. This suggests that such information may be even more important for firms that do not use AI already. Smaller manufacturers most often indicate that information services would be “helpful” or “very helpful”. Differences due to enterprise size are much less pronounced among enterprises in ICT.

#### Other public sector initiatives to support the uptake of AI

Looking to the future, enterprises were surveyed on the possible value of a wider set of public initiatives to foster the use of AI beyond information services, namely:

- investing in university education and vocational training in fields related to AI
- investing in retraining and lifelong learning for employees who work with AI

- improving understanding of AI among government officials
- gathering and publishing administrative public datasets
- promoting a competitive AI vendor market
- upgrading IT infrastructure, such as high-speed broadband.

The responses can be interpreted as enterprises' wish for more of the above initiatives. Most enterprises in the sample considered all the listed public sector initiatives "helpful" or "very helpful". Reiterating answers to previous questions, among the most widely and highly valued initiatives were those to develop human capital. Some 86% of enterprises considered that initiatives that foster investments in retraining and lifelong learning for employees who work with AI would be "helpful" or "very helpful". Similarly, 82% of enterprises considered public investments in university education and vocational training in fields related to AI to be "helpful" or "very helpful". In addition, but slightly less prevalent, the surveyed enterprises thought enhancing government officials' understanding of AI was important.

Some 78% of enterprises believe that any measures to foster a competitive marketplace for AI vendors would be "helpful" or "very helpful". By promoting a diverse range of vendors, enterprises might benefit from increased access to cutting-edge AI solutions and services. Public initiatives to upgrade IT infrastructure, such as high-speed broadband, are also supported by 78% of firms. Finally, 73% of enterprises perceive public sector initiatives that aim to gather and publish administrative datasets as "helpful" or "very helpful" for adopting AI. This finding emphasises the potential benefits of making administrative public datasets (more) accessible to firms.

Enterprises that use more AI applications are more likely to use all three of the following categories of public support: information and advice; training services; and measures that improve access to finance. Enterprises that report more obstacles to using cloud computing and AI are more likely to use public sources of information and advice but not training services or access to finance and subsidies. One possible way to understand these findings is that information scarcity is the primary barrier to surmount when adopting AI applications, whereas assistance for training and financial resources becomes pertinent only after adopting an AI application.

Enterprises that use AI intensively or face many obstacles to using AI find public services and initiatives more helpful than those that use AI less intensively or experience fewer obstacles to using AI. The generally positive view of possible public sector initiatives varies little in terms of industry and firm size.

#### Support to facilitate the management of regulatory change

The survey also elicited enterprises' views on AI-related regulation. Some uses of AI that involve autonomous systems might be detrimental to clients, potentially exposing businesses to legal jeopardy. One main message is that enterprises seek clarity with respect to accountability for the safe use of AI. While the desire for clear accountability is unsurprising, these findings underscore the need for policy makers to examine regulations for possible ambiguities and to assess how best to communicate regulatory information to firms.

### *Structured interviews and case studies reveal diverse approaches used by institutions supporting AI diffusion in firms*

Institutions for technology diffusion are public or quasi-public bodies that facilitate the spread and use of knowledge and methods to assist firms in adopting technologies. Some are well known, such as Germany's Fraunhofer IAO/IPA, the United Kingdom's Digital Catapult and the United States' Manufacturing Extension Partnership programme. Such institutions work to assist the adoption of many, frequently digital, technologies. Chapter 4 examines the types of support provided by diffusion institutions in respect of AI. All the institutions in question have established dedicated services to support the uptake of AI. The literature on AI adoption has barely explored the role of institutions in technology diffusion. Chapter 4 is based on evidence gathered through desk research, structured interviews and written contributions from 19 institutions supporting AI uptake in firms in G7 countries plus Singapore. AI Singapore was invited to participate as this organisation has employed several novel approaches to diffusion, from which valuable lessons can be drawn.

The interviews first aimed to characterise how each diffusion institution supports AI adoption. They then explored each institution's experiences and understanding of the main barriers to AI adoption in firms. Finally, interviewees were asked to describe the institutions' views on the most effective ways to support AI adoption.

### *Mechanisms used by diffusion institutions*

Chapter 4 identifies seven main mechanisms that diffusion institutions use to assist firms in adopting AI:

1. technology extension services, which can help firms define business problems to be solved and develop proofs-of-concept of how AI can help
2. grants for business R&D and public research, which can help mitigate some of the risks associated with developing AI
3. business advisory services, which give non-technical support to managers to improve their understanding of their firm's AI readiness, opportunities and challenges
4. networking and collaborative platforms, which aid in the development of public and private AI ecosystems, create demonstration effects and facilitate knowledge transfer
5. on-the-job training
6. information services
7. open-source code to help firms increase their AI capabilities.

Many diffusion institutions blend these mechanisms. Table 1.3 matches each of the 19 diffusion institutions in question to the services they provide.

## Table 1.3. Diffusion mechanisms (in blue) used by selected technology diffusion institutions

| Country | Institution | Tech extension services | Grants for business R&D | Business advisory services | Grants for applied public research | Networking and collaborative platforms | On-the-job training | Info services and open-source code |
|---|---|---|---|---|---|---|---|---|
| Canada | Vector Institute | ■ | | | | ■ | ■ | |
| Canada | SCALE AI | | ■ | ■ | | ■ | ■ | |
| Canada | National Research Council Waterloo Collaboration on AI, IoT and Cybersecurity | | | | ■ | | | |
| Canada | Forum AI Québec | | | | | ■ | | |
| France | Ministry of Ecology "AI and Green Transition" programme | | ■ | | | | | |
| France | Cap Digital | | | ■ | | ■ | | |
| Germany | Fraunhofer Institute for Industrial | ■ | ■ | ■ | | | | |

| Country | Institution | Tech extension services | Grants for business R&D | Business advisory services | Grants for applied public research | Networking and collaborative platforms | On-the-job training | Info services and open-source code |
|---|---|---|---|---|---|---|---|---|
| | Engineering IAO | ■ | ■ | ■ | | | | |
| Germany | German Research Centre for Artificial Intelligence | | | | ■ | | | |
| Germany | Plattform Lernende System | | | | | ■ | | |
| Germany | Mobility Data Space | | | | | | | ■ |
| Italy | Artificial Intelligence Research and Innovation Centre | ■ | | | | | | |
| Italy | SAIHub | | | | | ■ | | |
| Japan | New Energy and Industrial Technology Development Organization | | ■ | | ■ | | | |
| United Kingdom | National Health Service (NHS) AI Lab | ■ | ■ | | | | | ■ |
| United Kingdom | Digital Catapult | | ■ | ■ | | | | |
| United Kingdom | TechUK | | | | | ■ | | |
| United States | Manufacturing Extension Partnership | ■ | | | | | | |
| United States | Digital Manufacturing and Cybersecurity Institute | | ■ | | | | ■ | |
| Singapore | AI Singapore | | ■ | ■ | ■ | ■ | ■ | ■ |

### *Effective ways to support AI adoption identified by institutions for the diffusion of technology*

Institutions that support the diffusion of technology in business usually choose to work with firms certain initial capabilities and where AI is or can be part of the company's core business. To work with potential AI adopters, staff in diffusion institutions usually commence with an evaluation of firms' digital and AI proficiency. This evaluation may be conducted when assessing eligibility for grants for business R&D, during technical visits, and in workshops offering business advice. AI Singapore uses self-assessment tools to help firms gauge their capabilities and identify the assistance they require. For companies that are not sufficiently digitally mature, many governments have separate policy instruments offering dedicated support for digitalisation.

Some diffusion institutions only select AI projects with a clear path to increases in performance, product or service quality, or cost reduction. Interviewees explained that this increases the likelihood that a proof-of-concept will achieve tangible impacts, which helps to convince firms to scale up investments. However, other institutions consider that to begin, firms should not focus just on the ROI but should also value experimentation that may lead to subsequent breakthroughs.

Diffusion institutions broadly agree that preparing catalogues of applications, use cases, and success stories can help firms understand the possible gains from AI. Such catalogues help establish a record of success. They can document positive and negative experiences that other firms can learn from. Specifically, case studies that quantify the economic impact of investments (such as sales increases and cost reductions) can help to estimate the ROI. Catalogues or directories of this sort can also help managers better understand the opportunities, challenges and constraints posed by AI. Several of the diffusion institutions described in Chapter 4 compile such catalogues, including the Digital Manufacturing and Cybersecurity Institute (MxD), Plattform Lernende Systeme, the Forum IA Québec, Fraunhofer IAO/IPA and the NHS AI Lab.

Each of the following sections considers a specific mechanism that diffusion institutions use, i.e. technology extension services, grants for business R&D, business advisory services, funding for applied research, networking and collaborative platforms, on-the-job training, and data platforms and open-source services. Each section sets out the main observations on policy and institutional practices for the mechanism concerned.

### Technology extension services

In implementing technology extension services, interviewees suggested that diffusion institutions should work with firms in a sequence of steps: 1) establishing one or more business cases describing how to apply AI (for instance, clarifying how autonomous forecasting, decision support or decision making would help); 2) scoping possible AI solutions and assessing data maturity (for example, assessing if the business is gathering and processing the correct data); and 3) developing pathways to implementation. Several recommendations are evident for each of these steps:

1. Generic information on use cases can help advance a base understanding of AI in firms. However, to establish the business case for AI adoption, diffusion institutions need to obtain as much operational data from the firm as possible, mapping possible AI applications to firm-specific goals.
2. The staff of diffusion institutions should spend time at the firm to assess its digital maturity and simulate what an AI solution could do. Developing proofs-of-concept should begin by tackling more straightforward problems using readily available data. Staff can also help estimate the ROI for a more extensive AI project and help firms decide whether to invest in it. To this end, diffusion institutions highlight the need to have an economist join data engineers and other technical experts in technology extension projects.
3. An implementation roadmap should describe in detail what deploying a fully integrated AI solution across the organisation would entail. AI solutions can significantly impact various business processes and departments (e.g. accounting, purchasing and production). The roadmap should also describe How to ensure AI models perform well over time. The implementation plan should be co-developed with the firm's staff from the outset to secure co-operation and draw on employees' collective knowledge.

Technology extension services reportedly work best when firms assign their own staff and contribute in-kind resources. Projects can also involve other actors, such as universities and research institutes. Such collaborations can be particularly valuable in projects involving pre-commercial AI applications.

### Business advisory services

According to interviewees, business advisory services can be particularly effective in three main ways. First, they can help firms make initial estimates of the ROI using scenario analysis without necessarily going into the technicalities of AI. For instance, advisors can help managers estimate the downtime of machines or production lines and the financial savings to be made using predictive maintenance. Secondly, diffusion institutions can help raise awareness and understanding of any public support for AI adoption offered at national and international levels (e.g. EU calls). Firms are often unaware of such support, including funding opportunities. Thirdly, diffusion institutions can offer business advisory workshops to raise AI literacy among managers. They can also provide advice on ethics and regulation.

### Networking and collaborative platforms

Companies often have similar business problems and ways of using AI to solve them. Seminars and conferences can facilitate valuable exchanges between business executives and help raise understanding of the opportunities that AI presents and the types of transformation firms need to make. Seminars and conferences also facilitate networking between managers, researchers, trade associations, diffusion institutions, AI solution providers and other actors. Such events can help AI reach business sectors where adoption tends to be lower. They can also be used to gather the views of stakeholders in order to inform and shape policies and regulations for AI.

### Grants for business R&D and applied public research

Financial support can reduce the risks entailed in developing proofs-of-concept and exploring theoretical applications. As part of their allocation criteria, some grant schemes ask firms to indicate the expected ROI, or the cost reduction, expected of an AI system. Financial support can also help firms build a digital infrastructure for collecting, managing and processing data for AI, e.g. support for deploying IoT technologies. Some business sectors, such as fintech, already use AI intensively. However, when used to help acquire third-party AI applications, grants can encourage firms in other business sectors to work with AI solution providers. According to the interviewed diffusion institutions, grants that deliver the best outcomes require beneficiaries to match public support with their own resources (financial or in-kind). Similarly, publicly funded research projects reportedly produce the best results when companies assign their staff to the research team.

### On-the-job training

Training courses are essential for existing employees to gain the technical knowledge required for AI adoption. Tools for self-assessment of digital maturity, like AI Singapore's AI Readiness Index, can also be used to help managers, venture capitalists and solution providers identify use cases and design business models for AI solutions. Managers and technicians can also be trained in information governance, regulations and ethical issues. Such training can help tackle compliance and AI assurance concerns that often stop firms from using their data or prevent them from engaging with AI altogether. While on-the-job training can help firms address the scarcity of workforce skills in AI in the short term, various diffusion institutions consider that countries need to embed AI across tertiary education.

### Information services and open-source code

Open-source tools make AI methods and resources accessible to a broad audience beyond AI specialists and computer scientists. It is easier for statisticians, data engineers, physicists and other professionals with varied backgrounds to work with such tools than to develop algorithms from scratch. Diffusion institutions such as AI Singapore and NHS AI Lab use open-source resources together with other mechanisms, such as on-the-job training and technology extension services.

Particularly helpful for SMEs are publicly funded infrastructures that subsidise computing resources (e.g. hardware and cloud computing) and provide real or synthetic training data for free or at low cost. Such resources also need to be combined with other forms of support, such as business advice. For example, Digital Catapult's Machine Intelligence Garage gives SMEs access to computational resources in combination with mentorship and fundraising opportunities. By verifying the parties' identities and ensuring the integrity of data transfer, digital platforms and online marketplaces can also provide a trustworthy channel for secure data transfers. In addition, many firms underestimate the opportunities to establish data partnerships to tackle common problems, especially those involving competitors.

### *Findings from interviews with enterprises offer new insights on the role of public services for AI adoption in firms*

Chapter 5 reports the findings of interviews with senior staff working in firms in the two sectors addressed in the survey. The interviews aimed to elicit qualitative information to better interpret the quantitative data gathered through the survey.

Various of the interviewees came from enterprises that responded to the survey. Others were identified from a pool of over 600 candidate interviewees. The 15 interviewed experts hold positions such as chief information officer, chief technology officer, head of digital business, head of R&D, and chief technology officer, among others. There was an approximately equal representation among G7 countries and between the two surveyed sectors.

#### *Enterprises and data acquisition*

The interviews reveal that while many enterprises acquire data from research institutes and the public sector, they rely most on private data sources. The most common type of data acquired from public sources is generic data, such as demographic information, public company records, labour statistics and weather data. More specific and commercially valuable data sets from public administrations are rare. Private data sources are the preferred choice for most firms, as they offer more specialised and proprietary data that can provide a competitive advantage. In addition, more opportunities exist for providing feedback on data quality to private data sources than to public sources.

Procedural complexities in acquiring public data can impede data-driven decision making. These complexities often exist for legitimate reasons, such as maintaining data integrity and security, but can create inefficiency. Multiple layers of approvals, reviews and checks can lead to prolonged waiting periods, which can also render data obsolete when accessed.

In addition, data in public repositories are often too old for real-time applications. Many businesses must invest time and effort to validate the currency of public data. Policy makers need to ensure that data remain relevant and actionable. Using publicly sourced datasets can also be problematic due to vague terminologies and other shortcomings. The absence of comprehensive documentation can leave users to grapple with the data's true meaning and context. For example, a business might come across a large CSV or Excel file from a public source and encounter columns filled with terminology that is not easily understandable while lacking accompanying documentation for clarification. A common problem the interviewees reported is the data quality itself. For example, it is not uncommon to encounter discrepancies, conflicting information and missing data. Overall, policy makers need to ensure that shortcomings of the above sorts are addressed.

Interviewees generally considered that a centralised platform for public sector data access could streamline the search and retrieval process. A centralised hub could facilitate seamless transitions between databases, enhancing users' ability to access and link to specific studies or datasets.

Interviewees emphasised that the legal frameworks governing cross-border data flows could be made more compatible. International data sharing can be an intricate process, particularly if navigating diverse data-sharing laws. Different countries have distinct data protection and privacy legislation. This can pose challenges for companies that operate in multiple jurisdictions and need to comply with each region's specific and sometimes complex regulations.

Vendor certification is common across industries and could be adapted for data vendors. One interviewee noted that such certification would help to provide assurance and confidence in the data's authenticity and reliability. Especially for SMEs, checklists of the most important criteria to consider in vendor search and selection would be helpful.

### *Public services that support the adoption of AI*

#### Access to information or advice concerning the adoption of AI

Most interviewed experts affirm that the insights derived from public sector sources help to make informed decisions and shape business strategies. Access to information such as economic data, regulatory updates and compliance guidance is considered valuable. Such information is crucial in planning, analytics, market sizing, go-to-market strategies and understanding market dynamics.

Interviewees drew attention to a lack of consolidated information on private-sector AI software or services. Companies frequently receive use case solicitations from vendors, presented in marketing language. Governments might help by providing such information in more neutral ways. Several interviewees suggested that governments could provide guidelines or a framework to aid SMEs in navigating the vendor selection process, advising them on, for instance, the top ten considerations to consider when choosing an AI vendor.

Interviewees also pointed to challenges in accessing public sector information to facilitate AI development. They highlighted the frequent lack of clear pathways to specific public agencies. The absence of a one-stop interface and streamlined processes and the occasional fragmentation of channels to public services create challenges in identifying the right agency or programme to consult. Policy makers could help by establishing a consolidated platform or resource hub that streamlines access to AI-related public information, guidance and advice. Especially for SMEs, guidelines outlining agency roles and expertise and mechanisms for companies to communicate their needs would also enable more targeted and efficient exchanges.

#### Publicly provided or supported training services

Regardless of sector, all interviewees reported challenges in finding specialised AI talent. In the OECD/BCG/INSEAD survey, 58% of enterprises use public sector training services to help adopt AI. Interviewees who expressed a reluctance to use public sector training programmes emphasised the need for more specificity in the training offered. For instance, instead of generic AI training, they found greater value in programmes tailored to industry or business-specific needs. For example, manufacturers may prefer training in AI that focuses on optimising supply chain management.

Additionally, the experts highlighted the value of hands-on training oriented towards real-world projects. Workshops in which participants use AI tools and datasets in practical exercises related to their industry can significantly improve AI readiness.

Various interviewees asserted that public sector providers should collaborate with industry to design targeted training. Inviting industry professionals to share their experiences and insights can help develop practical training materials that resonate with private companies.

Reiterating the survey findings (Chapter 3), the interviewees observed that AI is often perceived as a broad, all-encompassing term, overlooking the existence of distinct subfields within it. Academic certifications may not provide the comprehensive information that employers seek. In this rapidly evolving field, there is a growing need for new qualification frameworks that effectively communicate precise and relevant information regarding candidates' capabilities and competencies to employers.

The interviewed experts agreed on the need for new AI curricula to meet the growing demand for skilled AI professionals. AI degree programmes often lack sufficient focus on industry-specific applications and practical skills. For example, a healthcare organisation may seek AI graduates who are well-versed in medical image analysis and diagnosis. Companies often seek AI professionals who can quickly apply their knowledge in the workplace. Consequently, curricula that incorporate practical components, such as internships or industry placements, are highly valued by employers.

### *External collaboration to develop AI*

#### Engaging with universities and public research institutions to develop AI

The 2023 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises* showed widespread collaboration with universities and public research institutions. More than half of the responding enterprises collaborate with university faculty members, PhD candidates, or postdoctoral students to advance AI development.

The interviewees reiterated the value of such collaborative partnerships. Firms can share their industry insights, practical experience and real-world datasets, enriching academic research. In turn, academic institutions can share their latest research, methodologies and theoretical advances, helping firms utilise cutting-edge research. Such partnerships can also provide access to advanced computing infrastructure and dedicated R&D teams, enabling firms to undertake more ambitious and resource-intensive AI projects. Firms can also enjoy opportunities for talent acquisition and development.

Collaborations between research institutions and firms, especially those in the ICT sector, frequently yield intellectual property (IP) and the associated IP rights. The interviewees noted that striking a balance between the interests of both parties regarding the ownership, usage and commercialisation of IP can be complex and may give rise to disagreements. Indeed, naturally, firms often focus on commercialisation and ROI, while academic institutions prioritise scientific discovery, publication and academic recognition. These differing goals and incentives can lead to conflicts regarding confidentiality and data sharing. One interviewed expert highlighted the potential benefits of developing a framework or model non-disclosure agreements to facilitate collaboration between firms and universities.

Most interviewees drew attention to the complexity of managing the distinct cultures, priorities and operational structures characteristic of corporate and academic environments. These diverse institutions typically have different approaches to decision making and timelines. Academic institutions often operate on longer-term research cycles, while firms operate in faster-paced, market-driven environments.

An obstacle mentioned in some interviews was the lack of transparency in how universities use the funding that firms provide, how other developments within universities might affect a project (such as a turnover in postdocs), and overall project governance. Delays, misunderstandings, and even conflict can arise without clear guidelines, transparent processes, and well-defined project governance structures.

One interviewee highlighted that centres of AI research predominantly focus on collaborations with medium and large-size enterprises. Dedicated programmes could help address specific challenges faced by SMEs, such as overall resource constraints and more limited access to AI talent.

Interviewees held that some public financial support for collaborations could help mitigate risks for firms. Public financial support might be limited to enterprises' first collaborative experience. Companies would also like less complex processes when applying for public funds that support AI research in collaboration with universities. Interviewees stressed the importance of enhancing transparency throughout the process. Clear guidelines, well-defined evaluation criteria, practical examples of successful applications and accessible information about funding opportunities would all help. Additionally, interviewees advocated for feedback loops to facilitate communication between funding agencies and applicants.

## *Chapter 6: Implementing the OECD/BCG/INSEAD survey in Brazil: key findings*

Chapter 6 reports the results of a survey on the use of AI in enterprises in the State of São Paulo, Brazil. São Paulo is the most populous State in Brazil and the largest economically. It also hosts an innovation ecosystem that includes Brazil's main universities and research centres, as well as many businesses in high-tech sectors.

The survey was conducted by SEADE, the official statistics and data production organisation of the State of São Paulo, in partnership with the Regional Center for Studies on the Development of the Information Society (Cetic.br), from the Brazilian Network Information Center (NIC.br).

The survey instrument was adapted from the OECD/BCG/INSEAD questionnaire, permitting comparison with the survey in G7 countries. The São Paulo survey had the same target populations of medium- and large-sized manufacturing and ICT enterprises. The survey adopted a probabilistic approach, meaning that it aimed to obtain results statistically representative of the entire population of enterprises in the state.

### *How enterprises in the State of São Paolo use AI*

The survey findings indicate that the use of AI among large and medium-sized enterprises in the manufacturing and ICT sectors in the State of São Paulo is relatively incipient. From a sample of 2 561 enterprises, only 167 (6.5%) were found to use AI actively. This corroborates previous research in Brazil, such as (Brazilian Network Information Center, Brazilian Internet Steering Committee, 2022[19]), which highlighted low rates of use of AI across enterprises of all sizes in all sectors. There is considerable room for expanding the use of AI, transitioning from point solutions to more integrated adoption, such as incorporating customer relationship management systems.

Among enterprises that actively use AI, 49% use it in customer-oriented services. The second most frequent application is in process control, automation and optimisation of production (44%), including such uses as predictive maintenance and automated support for programmers. These results broadly align with the findings from G7 countries. However, most enterprises surveyed in the State of São Paulo use only a few AI applications (58% of enterprises with just one or two AI applications compared to 4% in G7 countries).

Most enterprises in São Paulo procure solutions externally and exhibit a relatively low level of internal development. Some 28% of the surveyed enterprises use AI for R&D, considerably lower than in most G7 countries. A higher share of enterprises in São Paulo also considers AI of minor importance to main business processes (20%) than in G7 countries (8%). Moreover, managerial positions related to AI are still rare, even in enterprises that use AI.

### *Practices and partnerships to adopt and develop AI*

Particularly salient is the limited extent of partnerships with researchers. Only 6% of enterprises collaborate with undergraduate students, faculty, doctoral students or postdoctoral researchers, while partnerships with researchers outside of universities occur in only 5% of AI-using enterprises. By contrast, among G7 countries, more than 50% of enterprises have collaborated with university faculty, PhD, or postdoctoral students.

### *Expanding the uptake of AI and the role of the public sector*

Public authorities in Brazil have created many initiatives to support business innovation. However, none to date specifically target AI. As in G7 countries, most enterprises in the State of São Paulo would welcome one or another form of public support to help strengthen staff skills in AI. For instance, 64% of respondents assert that help to establish partnerships with educational and professional training institutions would be “very useful”. Regarding broader public sector initiatives to support the adoption of AI, investment in university education and professional training in AI is considered particularly important. Fully 75% of the enterprises declare that such policies would be “very useful”.

As in G7 countries, most enterprises judge that public information services could be “helpful” or “very helpful”. Some 62% of respondents consider that information on current or forthcoming regulations about data or AI would be “very useful”.

It is widely understood that IT infrastructure and connectivity problems in some regions of Brazil require public sector initiatives to be fully resolved. It is perhaps unsurprising that 73% of enterprises cite upgrading IT infrastructure, such as high-speed broadband, as “very useful” for adopting AI.

The survey findings suggest that benefits could come from creating support instruments that encourage partnerships around AI. Benefits could also be had from examining the suitability and current designs of innovation support instruments, with a view to identifying opportunities where adjustments might facilitate enterprises’ efforts to adopt and innovate with AI. Developing and/or strengthening a variety of possible information services might be a low-cost but relatively high-impact first step.

## Policy-relevant take-aways

This section summarises the study’s main policy-relevant take-aways. A key methodological caveat is that this report comprises a mix of cross-sectional survey data and information gleaned from interviews. The data analyses are correlational and cannot offer evidence on which sorts of policies are likely to be most cost-effective. **Several results merit further examination using other methods. For instance, it would be helpful to better understand causal relationships associated with public sector support to AI diffusion in business**. For example, is the tendency for enterprises that use AI more widely to also use public support services driven by their encountering more diverse adoption challenges? Or might it be because more alert leadership in an enterprise will both adopt AI more actively *and* seek external assistance more actively?

An overarching observation, evident from the studies reported in Chapter 2, is that **productivity benefits could come from accelerating rates of adoption of AI**. In all OECD countries (plus Brazil) rates of use are low in core business processes, particularly in smaller enterprises. Increasing uptake of AI matters because of the possible positive impacts on labour productivity. However, other benefits could also accrue, for instance with respect to environmental outcomes. AI can, for example, lower defect rates in production, reducing the need for material inputs. AI can also make many processes more energy efficient, for instance, by optimising logistics.

**Policy insights from this and comparable studies will likely become more important as AI adoption rates increase.** This is because the focus of this work has been on medium-sized and large enterprises as well as active users of AI. This focus provides insights that will be relevant to the numerically larger group of small firms that will aim to adopt AI. Indeed, the survey shows that enterprises that use more applications of AI are more likely to use a range of public support services. As the number of enterprises seeking to apply AI more widely grows, how public services and policies respond will become more consequential.

**A main and somewhat unexpected finding is that a significant share of enterprises have, at some point in time, used and valued various public services that can aid the adoption of AI positively**. The most frequently used services are those providing access to information or advice.

### *Addressing the need for skills*

The 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises* reiterates the findings of many previous surveys that a **scarcity of skills – particularly specialised talent – hinders uptake**. Even many large enterprises experience the same problem. **Initiatives to develop human capital are also among the most widely used and highly valued**.

Several results were obtained from the survey and interviews relevant to the **content of curricula in academic institutions as well as the content of training services**. All told, many **enterprises in search of increased AI skills feel they need a better practical understanding of how to identify and use the**

**right skills**. Academic certifications may not provide the comprehensive information employers seek in this rapidly evolving field. **Updated qualification frameworks could help** recruiters better assess how the AI skills possessed by holders of different qualifications can be applied in their businesses.

**Training programmes should be well tailored to industry or business-specific needs** (such as using AI to optimise supply chain management). **Particularly valuable is training on real-world projects using AI systems and datasets common in specific areas of business. Public sector providers should collaborate with industry to design training materials**.

**Curricula in some AI degree programmes might also incorporate a greater focus on industry-specific applications.**

**Policy makers should likewise examine where enhancing government officials' understanding of AI could have the greatest effect**. The survey indicated that some enterprises consider that strengthening these skills would be beneficial, but this study was unable to explore the topic in more detail.

### *Public data and data policies*

**Policy makers need to be alert to the quality of data in public data repositories**, ensuring, for example, that there is no conflicting information. **Procedures facing enterprises seeking to acquire public data should be reviewed and, where possible, simplified.** Irrespective of procedural complexity, data from public repositories is often too old for real-time use. **Policy makers should ensure that data remains current and actionable**.

Data in public datasets can also be problematic due to vague terminologies and other shortcomings. **Documentation should be available such that users of public data can easily comprehend its meaning and context**.

**Centralised platforms for public sector data access could streamline the search and retrieval process**.

**Policy makers should seek to enhance the compatibility of legal frameworks governing cross-border data flows.** International data sharing can be an intricate process and poses particularly acute challenges for companies that operate in multiple jurisdictions.[1]

Consideration could be given to **developing checklists for SMEs to help them select the most suitable private data vendors**. The aim would not be for public authorities to identify preferred vendors but to help SMEs evaluate which vendors best suit their needs.

### *Collaboration with universities and public research organisations*

To aid the use and development of AI, **collaborations with universities and public research institutions are widespread, valued and have several purposes. Some public financial support for collaborations could help mitigate risks for firms. However, public financial support might be limited to enterprises' first collaborative experience. R&D tax credits might be used to encourage industry-university collaboration and research commercialisation**. In several countries, R&D tax credits are designed to provide significant additional incentives for collaborative research, above and beyond the tax credit received when R&D is undertaken in-house. Collaborative R&D has been shown to positively affect the technological capacity of firms even after controlling for the possibility that more dynamic firms might also collaborate more often (Barajas, Huergo and Moreno, 2011[24]).

**Processes for applying for public funds that support AI research in collaboration with universities should be simplified. Information could be made widely available to enterprises, clearly describing funding opportunities, evaluation criteria and examples of successful applications. Feedback loops to funding agencies could also help**.

As seen in many studies, including those unrelated to AI, firms and research bodies typically have different goals, working practices, implementation schedules and interests. This perennial issue invites policy attention to the **possible benefits of developing model framework agreements for the benefit of both parties to facilitate collaboration between firms and universities**.

**Universities and public research organisations themselves could seek to ensure transparency in key operational practices**, including how the funding that firms provide is used, how other developments within universities might affect a project (such as a turnover in postdocs), and overall project governance.

### *Information and advisory services provided by the public sector to assist in the adoption of AI*

A large majority of enterprises judge that information and advice provided by specialised public bodies could help their use of AI. Even though many of the sampled enterprises use AI in quite advanced ways, they still seek additional information on various domains of AI. This suggests that **policy makers should look for cost-effective ways of delivering easily findable, accessible, current and specific information and advice**, for instance, on regulatory updates, compliance guidance and evolving business use cases for AI.

**Governments could provide guidelines or a framework to aid SMEs in navigating the vendor selection process**, advising them on, for instance, the principal considerations to be aware of when choosing an AI vendor.

**Policy makers could help by establishing a consolidated platform or resource hub that streamlines access to AI-related information, guidance and advice from public agencies**. Especially for SMEs, guidelines outlining agency roles and expertise, along with **mechanisms for companies to communicate their needs**, would also help.

One main message is that enterprises seek clarity with respect to accountability for the safe use of AI. While the desire for clear accountability is unsurprising, these findings underscore **the need for policy makers to examine regulations for possible ambiguities and to assess how best to communicate regulatory information to firms.**

### *Other obstacles to using AI*

The survey data suggest that **IT infrastructure deficits, such as a lack of high-speed broadband, require examination and possibly a policy response**.

### *Institutions supporting AI diffusion in firms*

Institutions dedicated to facilitating the uptake of digital technologies, including AI, in firms are present in most, if not all, OECD countries. **This study offers insights on good practice in the programmes they implement and may be of particular interest to policy makers looking to review, create or expand such organisations.** The insights on operational practices are described in greater detail earlier in this chapter, and encompass:

- **Technology extension services**, for instance, as concerns a sequence of steps that might be followed in implementing extension services, raising AI literacy among managers, helping estimate ROIs using scenario analysis, and providing advice on ethics and regulation.
- **Networking and collaborative platforms**, for instance, in facilitating exchanges between business executives, helping increase understanding of the types of transformation that firms need to make, and gathering feedback for policy makers.

- **Grants for business R&D and applied public research**, for instance, helping firms to estimate the costs and benefits of an AI system, and the role of resource sharing on the part of beneficiaries.
- **On-the-job training**, for example, providing tools for self-assessment of digital maturity, training in information governance, regulations and ethical issues.
- **Information services and open-source code**, for instance, in helping SMEs gain access to computing resources (e.g. hardware and cloud computing), as well as real or synthetic training data, for free or at low cost.

### *Improving the evidence base for policy*

**Policy makers should examine the size of the impact of diffusion institutions relative to the goal of accelerating the uptake of productivity-enhancing technology across the economy**. Most institutions considered in this study do not work with large numbers of client firms. In one or two cases, they only engage with tens of enterprises a year. Most OECD countries now have national AI strategies. These often assert that the widespread adoption of AI is a strategic economic aim. However, the flagship institutions working to diffuse AI in business are small relative to the challenge. **Policy making could benefit from more systematic economic evidence on the direct and indirect effects of these institutions**. For instance, if they only work with a tiny percentage of the enterprise population, does their work nevertheless create wider demonstration or other secondary effects? If so, are those secondary effects large or small?

A policy-relevant contribution of this study is the development and cognitive testing of novel survey questions addressing such topics as enterprises' use and assessment of services and policies relevant to AI uptake. As noted earlier, **several NSOs helped shape the survey questionnaire, and various of the new questions it contains might be considered for inclusion in future surveys**.

As described in Chapter 2, prior studies highlight **the need to better understand the international comparability of surveys of AI in firms**. Differences in methodology may have created measurement discrepancies. Greater assurance of comparability will help to better inform policy.

Regarding the OECD/BCG/INSEAD questionnaire, a future development could be to expand the scope of research to enterprises that do not currently use AI but intend to do so or are in the initial steps of implementing AI. This would help to better understand the difficulties experienced in using AI and how these difficulties manifest in the different phases of implementation, such as in decision making around investments, the organisation and management of data, equipment acquisition and staff hiring. Such a shift to broader themes on AI uptake would be especially important in contexts where the overall use of AI in the corporate sector is low.

Regarding data collection, in a future iteration of the survey, it could be helpful to identify in advance specifically qualified persons in the responding enterprises to answer the questionnaire. This is because the survey encompasses varied and specific topics, from implementation obstacles to insights into the most helpful support services for the enterprise. An alternative would be to consider having more than one respondent, as the topics addressed may be the responsibility of more than one team within the enterprise.

The enterprise survey has an exploratory character. Budgets permitting, it could eventually be implemented, with possible revisions, across a wider set of countries, sectors, and number of enterprises, and using a sampling frame and probabilistic method allowing generalisation to national populations of enterprises. Doing so would strengthen cross-country and cross-firm statistical analyses.

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## Notes

[1] The OECD is undertaking a broad set of analytic and policy initiatives on cross-border data flows. A landmark achievement is the *Recommendation of the Council on Enhancing Access to and Sharing of Data* (OECD, 2021). Adopted on 6th October 2021, the Recommendation provides the first internationally agreed upon set of principles and policy guidance on how governments can maximise the cross-sectoral benefits of all types of data while effectively protecting stakeholders' rights (OECD, 2021[25]).

# 2 An overview of prior research on the diffusion of artificial intelligence in firms

This chapter draws together diverse types of information on the diffusion of artificial intelligence (AI) at national, sector and firm levels. It concentrates on AI in manufacturing and information and communication technology, the same sectors examined in the OECD/Boston Consulting Group/INSEAD survey conducted in 2022-23. This review provides an evidence base against which to assess the survey findings (presented in Chapters 1, 3 and 6). Most of the prior evidence indicates that, at least prior to the advent of generative AI, the adoption of AI in firms is an exception rather than the norm. Single-digit adoption rates for entire sectors are common in many countries. A universal finding is that adoption is highest in larger firms. The chapter also shows discrepancies in adoption rates across countries. More work is needed to understand the reasons for these divergences, which, among other things, are likely to reflect methodological issues in measurement.

## Introduction

Prior survey evidence has compared internal and external barriers to AI adoption, and shows that despite many commonalities, national differences also exist. An issue that merits further examination, given its policy ramifications, is why firms in many studies (but not all) indicate that cost is a barrier to adoption, and demand more public financial support for adoption. The enterprise-level interviews discussed in chapter 5 examine this topic further.

Prior studies also underscore the role of digital readiness as a condition for adopting AI. An adoption hierarchy exists whereby digital-intensive firms tend to apply AI in deeper ways. A six-stage model of the readiness journey – used to inform a survey exercise in the United States – is outlined in this chapter. This chapter also presents evidence rarely commented elsewhere on the importance of competition in the AI vendor market. More competition among AI vendors could induce technology providers to maintain high levels of operational quality, lower prices for customers, develop specialisations, serve previously underserved industries, and make technology available to a wider range of markets. Relative to the United States, the European Union may be lagging in terms of numbers of AI vendors. Data on venture capital (VC) investment also show that AI vendor firms' participation in VC deals is significantly lower in Europe than in the United States.

This chapter begins by reviewing data on the extent of AI adoption and diffusion among enterprises in the Group of Seven (G7) countries, the European Union and Brazil. It next assesses the barriers to greater AI adoption and diffusion in these countries.

## Assessing the extent of AI adoption and diffusion in enterprises across countries

This section examines the available literature on AI adoption in enterprises across several countries based on data provided by national statistical agencies, the US federal government, and the European Union. Overall, it finds significant diversity in the state of AI deployment across countries. Overall, however, the extent of AI uptake across firms is relatively limited. A further and consistent finding is that larger enterprises significantly outpace smaller ones in deploying AI technologies.

### *Canada*

Canada's 2019 Survey of Innovation and Business Strategy addressed a sample of firms and industrial non-profit organisations with at least 20 employees and CAD 250 000 (Canadian dollars) in revenue (Canada, Statistics, 2019[1]). Responding firms were sorted into 1 of 14 sectors (by the North American Industry Classification System [NAICS] code) and 1 of 3 size classes (20-99 employees, 100-249 employees, and 250+ employees). Questions covered the period 2017-19. The questionnaire was designed so that definitions of the innovation concepts used were consistent with those used by the OECD and Eurostat. Participation in the survey was mandatory under Canada's Statistics Act.

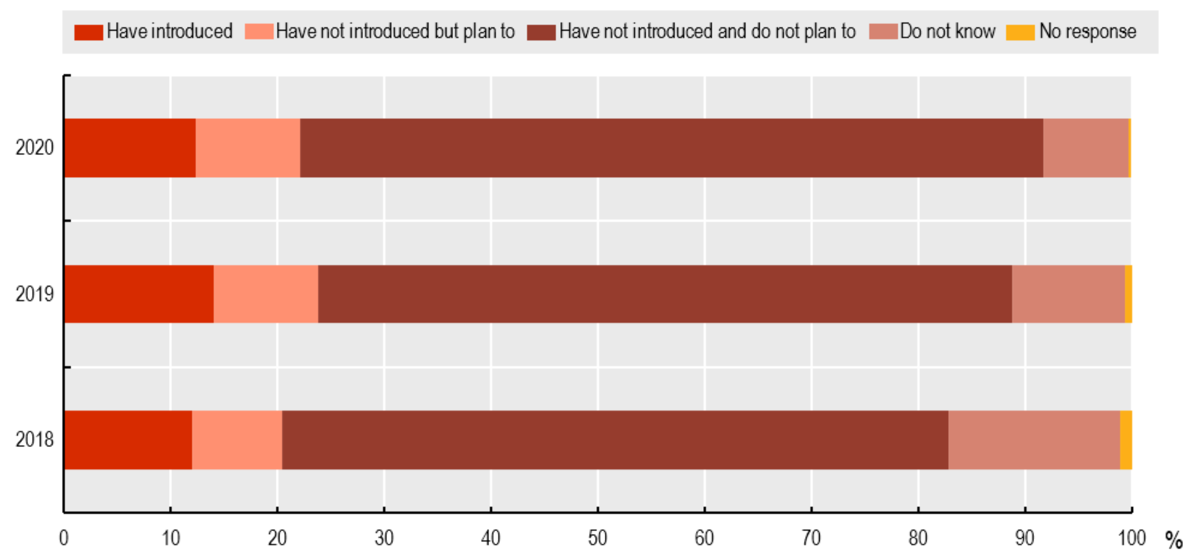
The three leading industries in Canadian AI adoption were: 1) information and culture (18% of all firms); 2) finance and insurance (21%); and 3) professional, scientific and technical services (21%). The largest Canadian firms have the highest rates of AI uptake, as in other countries.

Firms in leading AI adopter industries report a much greater shortage of computer science, information technology (IT) and general data science and analytics skills than in other industries. Shortages reported in the manufacturing sector were nearly identical to those for all industries. Excluding finance and insurance, the greatest shortage was of computer scientists, followed by persons with skills in general data science and analytics, and then IT.

### *Japan*

Japan's Ministry of Internal Affairs and Communications (MIC) compiled its Communication Usage Trend Survey (CUTS) in 2020 (MIC, 2021[2]). The survey aimed to gauge the development of information and communication networks and trends in information and communication technology (ICT) adoption. The 2020 CUTS received responses from 6 017 companies. Surprisingly, the share of all firms (with at least 100 employees) using AI and Internet of Things (IoT) fell from 14% to 12% from 2019 to 2020 (see Figure 2.1). It is striking that the share of firms reporting that they do not know whether they will adopt these technologies halved between 2018 and 2020 (from 16% to 8%). The share of firms reporting that they have not and do not plan to adopt AI and/or IoT increased from 63% in 2018 to 70% in 2020.

**Figure 2.1. Share of Japanese firms by AI and/or IoT usage, 2018-20**

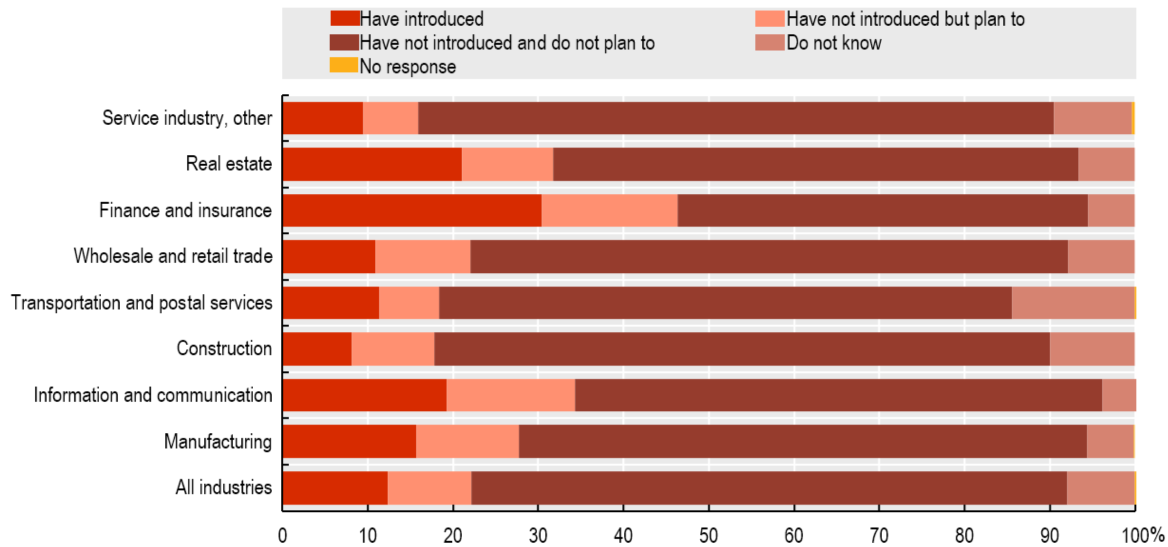



Source: MIC (2021[2]), 2020 Communication Usage Trend Survey, Ministry of Internal Affairs and Communications, http://www.soumu.go.jp/johotsusintokei/statistics/pdf/HR202000_002.pdf.

Manufacturing, information and communications, finance and insurance, and real estate have above-average AI adoption rates in Japan. Unsurprisingly, the finance and insurance industry leads all industries in both the share of firms using AI and IoT and those that do not use these technologies but plan to (see Figure 2.2). Overall, the survey indicates that 12.4% of Japanese firms use AI and/or IoT. Again, a clear positive relationship exists between the likelihood of using AI and IoT and firm size. The use rate in the 100-299-employee size class is half the rate of the group with 1 000 to 1 999 employees (10% and 22%, respectively). Similarly, the rate of AI use in the group of firms with 1 000 to 1 999 employees is less than half of that in firms with 2 000 or more employees (at 22% and 48%, respectively) (see Figure 2.3).

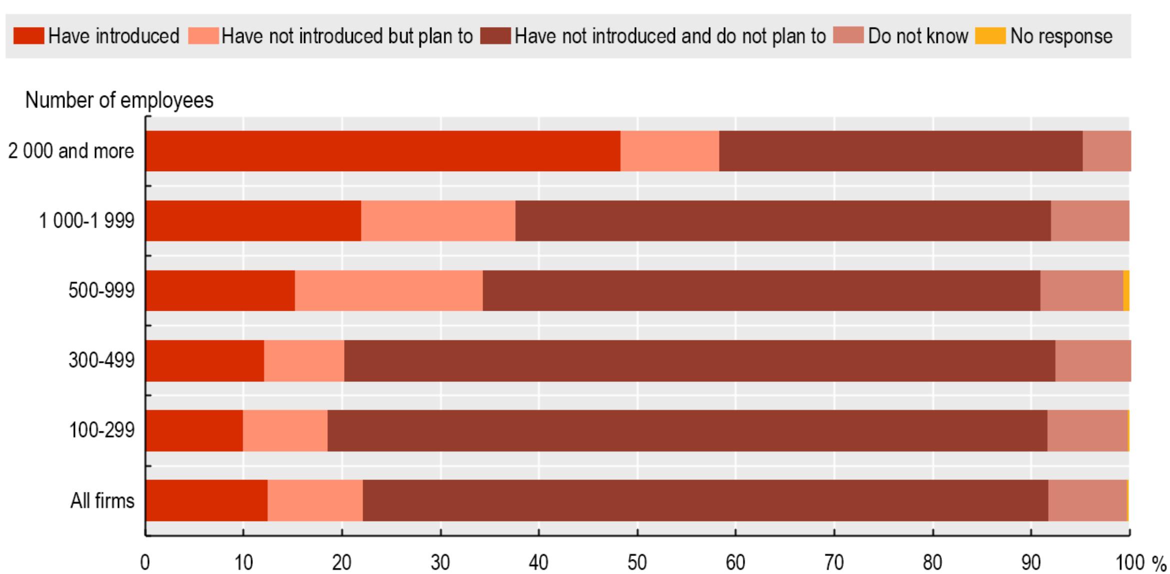
Some 69% of Japanese firms use cloud computing to some degree (up from 58% in 2018). Between 2018 and 2020, the share of firms not using cloud services and not planning to fell from 21% to 16%. Unsurprisingly, usage of cloud services is most common among Japanese firms in ICT (92%), followed by firms in the real estate and finance and insurance industries (86% and 81%, respectively). Japanese manufacturing has a slightly below-average share of firms using cloud computing services at 68% compared to the 69% economy-wide average. However, manufacturing also has an above-average share of firms not using cloud computing but planning to (12% compared to the average of 10%). More than half of Japanese firms report a shortage of ICT-related human resources (e.g. computer programming or data science skills). Only 15% of firms report that their current workforce has enough of these skills. The largest ICT skills shortage in Japan is for network operators. Across all Japanese industries, over 60% of firms reporting a shortage of human resources in ICT report a shortage of network operators. In all industries except for finance and insurance, the second-most prevalent shortage is of systems engineers, followed by data scientists.

### Figure 2.2. Share of Japanese firms by AI and/or IoT usage by industry, 2020




Source: MIC (2021[2]), 2020 Communication Usage Trend Survey, Ministry of Internal Affairs and Communications, http://www.soumu.go.jp/johotsusintokei/statistics/pdf/HR202000_002.pdf.

### Figure 2.3. Share of AI and/or IoT use in Japanese firms by firm size, 2020




Source: MIC (2021[2]), 2020 Communication Usage Trend Survey, Ministry of Internal Affairs and Communications, http://www.soumu.go.jp/johotsusintokei/statistics/pdf/HR202000_002.pdf.

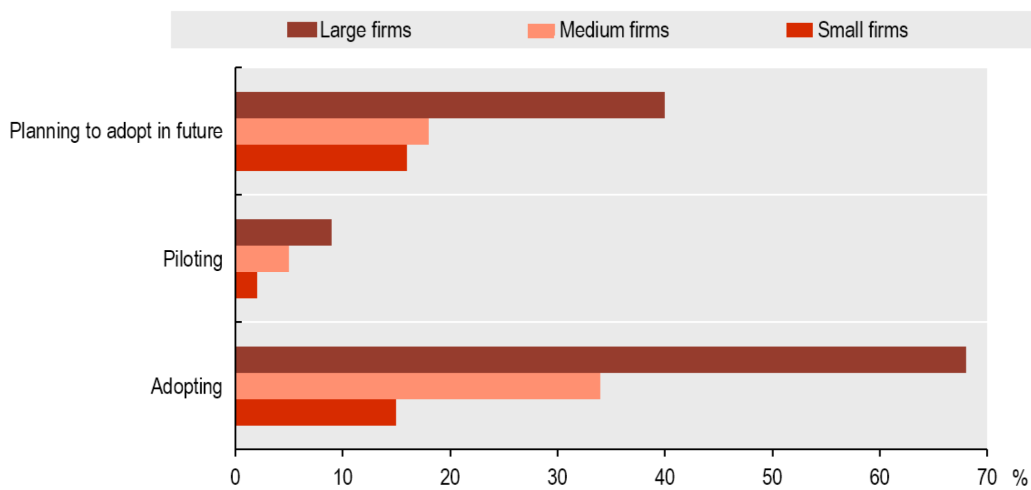
### *United Kingdom*

A 2022 survey conducted for the United Kingdom's Department for Digital, Culture, Media, and Sports queried 2 019 businesses in England, Scotland and Wales about their current and planned adoption of AI

(Evans and Heimann, 2022[3]). Participants were asked about their usage or planned use of the following technologies: 1) robotic processes automation; 2) machine learning; 3) natural language processing and generation; 4) data management and analysis; 5) computer vision and image processing; and 6) hardware related to AI.

As in other countries, AI adoption rates are strongly associated with firm size. The survey found that 15% of small firms adopted AI, compared to 34% of medium-sized firms and 68% of large firms. Compared to those adopting AI technology and those planning to do so in the future, the share of firms in the piloting stage was quite small. Only 2% of small firms, 5% of medium-sized and 9% of large firms were piloting AI (see Figure 2.4). Larger firms that have adopted AI technology are also more likely to have adopted multiple AI technologies. Notable in this survey is the high adoption rate among medium-sized and large firms compared with survey findings in other countries. In general, the size of such disparities between a number of cross-country surveys suggests that different methodologies or sampling frames limit comparability (see the discussion below). In such cases, the most useful insights from the national survey relate to inter- and intra-sectoral findings (such as, for example, differences in adoption by firm size and age).

### Figure 2.4. Share of UK firms adopting or planning to adopt AI technologies by firm size, 2020




Source: Evans A. and Heimann A, (2022[3]), AI Activity in UK Businesses Report, Capital Economics and DCMS, January 2022, http://www.gov.uk/government/publications/ai-activity-in-uk-businesses.

According to the same survey, data management and analysis is the most common AI-related technology adopted in the United Kingdom for all firm sizes, used by more than half of AI-adopting firms in each size class. In fact, the order of the five technologies by share of AI-adopting firms using them is the same for all three size classes (small, medium, large), with natural language processing (NLP) and natural language generation being the second-most-common use, followed by machine learning (ML), computer vision and image processing/generation, and then hardware.

From a sectoral perspective, the United Kingdom's legal sector has the highest adoption rate and share of firms planning to use AI technology. This is followed closely by the IT and telecommunications sector, with approximately three in ten IT and telecommunications firms having adopted AI. Manufacturing has the sixth-highest adoption rate, with fewer than one in five firms being current adopters and only 14% planning to adopt AI technology.

In total, AI-adopting firms in the United Kingdom invest the equivalent of around 9% of turnover on AI. Some 73% of those expenditures (6.6% of turnover) go toward AI-related labour, and the other 27% (2.4% of turnover) go to AI technologies. Interestingly, AI expenditures as a share of turnover are not strictly related to firm size. The study's authors suggest that medium-sized AI-adopting firms in the United Kingdom spend so much more of their turnover on AI because they are more likely to develop AI technologies in-house than small and large AI adopters.

### *United States*

#### *Findings from the National Science Foundation*

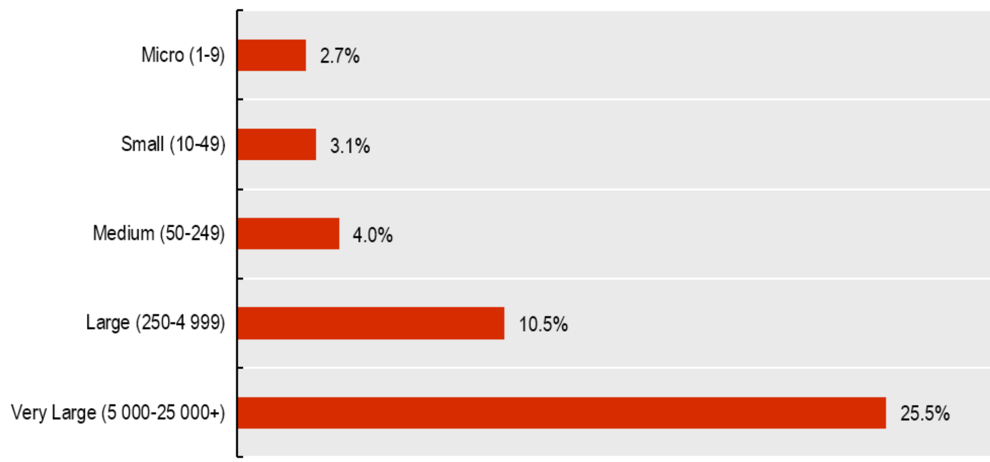
At writing, the National Science Foundation's (NSF) 2020 Annual Business Survey (ABS) (National Science Foundation, 2021[4]) is the most current and comprehensive assessment of AI adoption in US industry. The technology module of the survey contained three detailed questions regarding: 1) the availability of information in digital format (digitalisation); 2) expenditures on cloud computing services; and 3) the use of several advanced "business technologies", including a number typically categorised as AI, including: augmented reality, ML, machine vision, NLP, voice recognition software, robotics and automated vehicles (McElheran et al., 2021[5]).

Overall, the US ABS data show that AI adoption across almost all US industries remains very low. An analysis of the data by Zolas et al. (2020[6]) finds that across AI-related technologies for all firms in the US economy, the aggregate AI adoption rate was 6.6%. The ABS data show that the adoption of the mentioned AI technologies ranges between 83.2% to 85.8%. Some 89% of US manufacturers report not using AI at all. In fact, in key manufacturing industries such as machinery, electronic products and transportation equipment, fewer than 12.4% of companies report using AI as a production technology in any capacity. Reported use of AI by US companies in non-manufacturing sectors was likewise low. For instance, only 3.2% of US enterprises in professional, scientific, and technical services reported using AI. Only 2.2% of companies in the finance and insurance sector used AI. For firms in healthcare and social assistance, and educational services, the adoption rates were 5.7% and 2.0%, respectively.

While overall adoption of AI is low, the US ABS data show that larger companies are the leading AI adopters. The 2019 ABS surveyed 850 000 nationally representative firms on the use of AI as a production technology, receiving 590 000 responses for the period 2016-20 (NSF, 2019[7]). More than 25% of the largest companies use AI tools to create high-quality goods and services, compared with only 3-4% of small and medium-sized enterprises (SMEs) (see Figure 2.5). The results show that smaller US enterprises are lagging in the utilisation of advanced technologies, which is concerning when companies with under 500 employees contribute around 43% of US gross domestic product (GDP) (Kobe and Richard, 2018[8]).

Several reasons help explain why larger firms adopt AI more than smaller firms. For one, ICT adoption is higher in larger firms, and AI adoption relies on advanced use of ICT. For another, because large firms tend to serve large markets, they can better amortise the fixed costs associated with employing AI production technologies over more sales, lowering the unit costs of production. Furthermore, because a share of the talent needed to harness AI is foreign-born, larger companies can better afford the time, fees, and personnel resources inherent in the US visa process to attract AI workers. Larger firms also offer higher wages and more benefits, increasing the pool of top AI talent these firms can access. Finally, because vendors of AI systems benefit from supplying companies with a large consumer base, vendors may focus on creating relationships and contracts with larger firms, helping these firms better understand the value that AI systems can bring to their businesses. Zolas et al. (2020[6]) also argue that, until recently, with the greater use of cloud computing (a problematic topic for some of the enterprises surveyed by OECD/BCG/INSEAD, as discussed in Chapter 3), the extensive computing power required for large-scale AI applications was beyond the means of most firms, making AI more feasible for larger firms. Beyond firm size, Zolas et al. (2020[6]) also noted a relationship between firm age and AI use. For small firms (here, meaning those with fewer than 50 employees), use rates tended to decline with age, with the oldest firms having the lowest adoption rates, suggesting that it may be the "new, young, born-on-the-web firms" that are the main AI users. However, for larger firms (here, meaning those with over 50 employees), use rates exhibited the opposite pattern: as firm age increased, usage rates also increased, with the highest usage rates found in the oldest and largest firms. Overall, firm size appears to be a significant predictor of firms' AI use (Fleming, 2023[9]).

**Figure 2.5. Percentage of US companies using AI as a production technology for goods and services by company size, 2016-18**




Note: Numbers in parentheses represent the number of employees per company.
Source: NSF (2019[7]), Annual Business Survey: 2019 (Data Year 2018), National Science Foundation, https://ncses.nsf.gov/pubs/nsf22315.

### *Findings from the US Patent and Trademark Office*

The US Patent and Trademark Office (USPTO) (2020[10]). studied the volume, nature and evolution of AI and its component technologies using US patents from 1976 through 2018. The report describes an AI patent landscape over that period. The numbers presented in the USPTO study provide insights into the diffusion and adoption of AI in firms, even though patenting activity includes more than just firm-based innovations. When the USPTO examines a patent application, it reviews its technical content and assigns the patent to a specific technological grouping that has more than 600 subclasses covering a vast array of technologies. Key findings from the USPTO research include that, in the 16 years from 2002 to 2018, annual AI patent applications increased by more than 100%, rising from 30 000 to more than 60 000 annually, and that over the same period, the share of all patent applications that contain AI grew from 9% to nearly 16%. Moreover, the USPTO found an increasing "diffusion of AI across patent technology subclasses," essentially referring to increases in patenting of discrete applications of AI such as NLP and ML. The USPTO found that, in 1976, patents containing AI appeared in about 10% of the subclasses, but by 2018, they had quadrupled to spread to more than 42% of all patent technology subclasses. These figures suggest a broad and deepening engagement with AI technology within the business sector, not only in terms of quantity but also in the diversity and sophistication of applications.

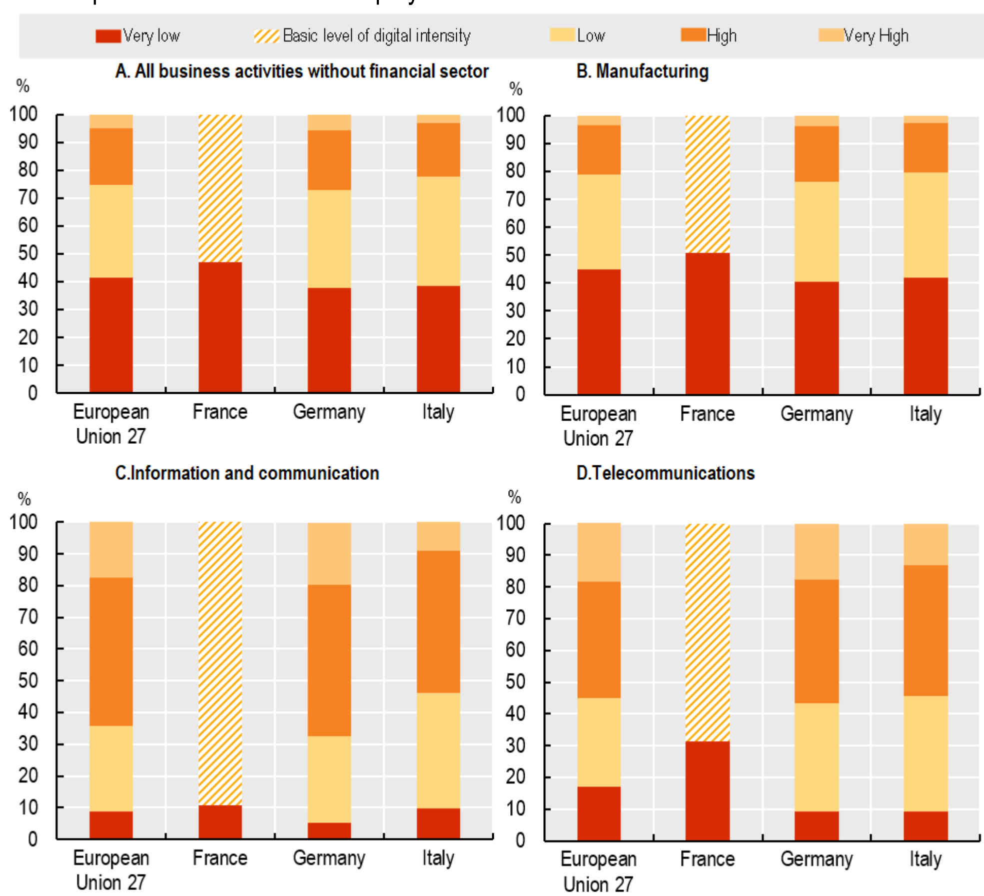
The USPTO report also offers data on the diffusion of AI patents across geography, finding that while the leading metro areas like the San Francisco Bay Area, southern California, and the Northeast Corridor still lead, the data since 2001 show that AI technologies are diffusing widely across US states and counties. Lastly, the report notes that several of the leading AI-patent-receiving firms today are not just the AI-technology producers (like IBM or Microsoft) but firms such as Bank of America, Boeing, and General Electric that are developing their own unique AI tools for their specific needs. A separate study suggests that US enterprises' AI adoption has accelerated recently, in part as a response to the coronavirus (COVID-19) pandemic.[1]

### *Europe*

The most statistically representative data on AI adoption in European countries is the Eurostat database, with a sample size of 142 000 representatives of enterprises and a median 80% response rate (Eurostat, 2022[11]). Eurostat data yield insights on the level of technology use in companies and the state of workforce preparedness for AI. France, with about 47% of firms with very low digital intensity, not only underperforms Italy and Spain (each at 39%) and Germany (38%) but also the EU average (41%) (see Figure 2.6, Panel A), which could pose challenges for the shift to more productive operations using AI. Unsurprisingly, the ICT sector is much more digitised than European economies overall (Panel C), as IT requires digitisation to function effectively. The telecommunications sector enables 5G mobile networks that can enhance the benefits from AI and accelerate adoption. France's telecommunications sector, with 10.7% of firms having very low levels of digitisation, is lagging major economies such as Germany (5.1%) and Italy (9.8%), as well as the EU average (8.8%). Only 22% of firms in the European Union have high or very high values for digital intensity.

## Figure 2.6. Digital Intensity Index for a selection of European countries, 2023

Percentage of enterprises with ten or more employees

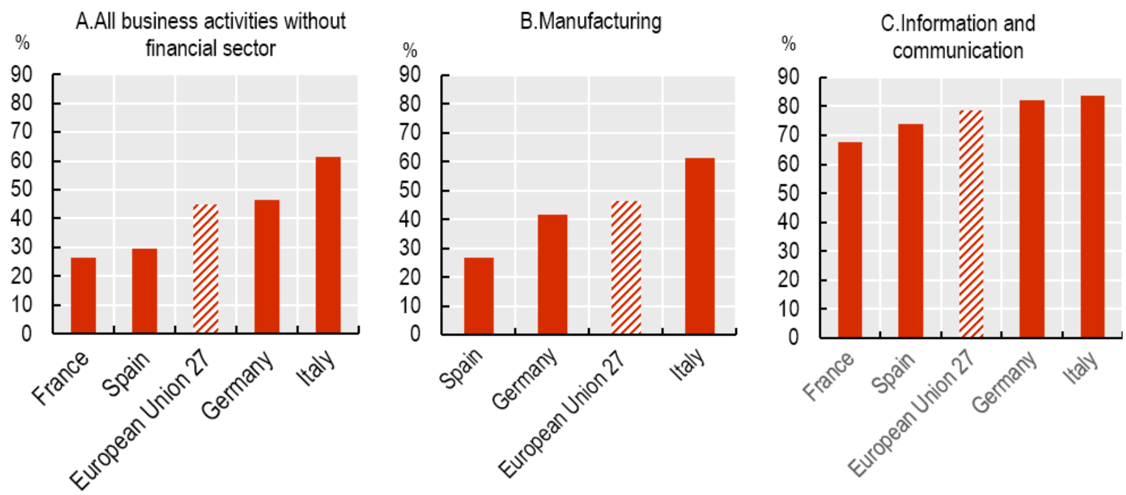



Note: The Digital Intensity Index (DII) is a composite indicator derived from the Survey on ICT Usage and E-commerce in Enterprises. The DII is one of the key performance indicators in the context of the Digital Decade, which sets out Europe's ambition on digital, laying out a vision for the digital transformation and concrete targets for 2030 in the four cardinal points: skills, infrastructures, digital transformation of businesses and public services. The 2030 target of the Digital Compass is that more than 90% of EU SMEs should reach at least a basic level of digital intensity. The indicator is useful to describe the extent to which EU enterprises are digitalised. It measures the use of different technologies by enterprises. The different definitions of the DII can be found at https://circabc.europa.eu/ui/group/89577311-0f9b-4fc0-b8c2-2aaa7d3ccb91/library/84b390d2-6a83-4dae-8aba-37c18557eb5b/details.
Source: Eurostat, Digital intensity by NACE Rev2 activity, ISOC_E_DIIN2, Percentage of enterprises, https://ec.europa.eu/eurostat/databrowser/view/ISOC_E_DIIN2, (accessed on March 2024).

In terms of buying cloud computing services, Italy performs well (see Figure 2.7, Panel A). Its share of enterprises buying at least one type of cloud computing service (61%) is higher than that of the European Union (45%) and Germany (46%). France underperformed in 2023 with 27% of enterprises. For the ICT sector, Italian enterprises demonstrate a strong propensity for embracing cloud technologies services, with the highest share at 84%; Germany closely follows, with 82% of enterprises buying at least one cloud service. France (68%) and Spain (74%) underperform the EU27 average, which stands at 79% (Panel C).

## Figure 2.7. Share of enterprises buying at least one cloud computing service in a selection of European countries, 2023

Percentage of enterprises with ten or more employees and self-employed persons

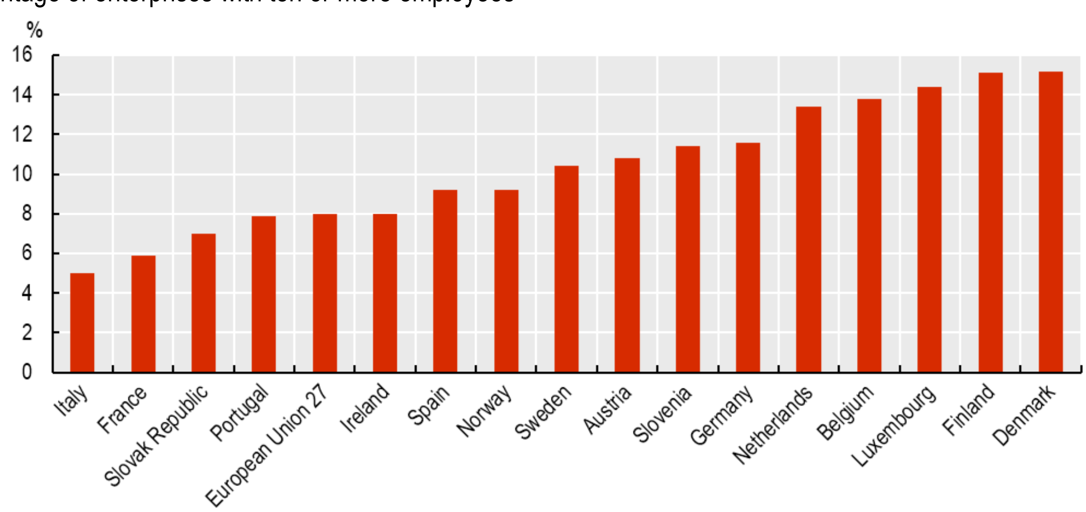



Source: Eurostat, Cloud computing services by NACE Rev.2 activity, https://ec.europa.eu/eurostat/databrowser/view/isoc_cicce_usen2, (accessed on March 2024).

In 2023, Denmark and Finland led the European Union with the highest share of enterprises utilising at least one AI technology, both standing at about 15% (see Figure 2.8).

## Figure 2.8. Share of enterprises that use at least one AI technology in a selection of European countries, 2023

Percentage of enterprises with ten or more employees




Source: Eurostat (2025[12]), Artificial Intelligence by size class of enterprise, https://doi.org/10.2908/ISOC_EB_AI.

On the other hand, Italy and France have relatively lower shares, with only 5% and 6% respectively. German enterprises showcase a higher usage of AI technologies at 12%, positioning it above the EU average of 8%. A separate study covering all firms in Germany found that only 5.8% used AI in 2019 (Rammer, Czarnitzki and Fernández, 2021[13]).

A survey commissioned by the European Commission (Gossé, Hoffreumon and van Zeebroeck, 2020[14]). found, unsurprisingly, that IT is the sector with the highest rate of AI adoption, with 63% of enterprises in this sector adopting at least one AI technology. IT is followed by education (49%) and manufacturing and human health (both with 47%). Transport is the sector with the lowest AI adoption rate (36% of enterprises). Though only 40% of enterprises in Europe's finance and insurance sector have adopted AI technologies, 27% plan to do so in the future, which is a higher share than for any of the other sectors considered.

The same survey suggests that among European enterprises that have adopted AI technologies, purchasing ready-made systems is the most common procurement method; nearly three in five adopting enterprises have opted for this method. This is followed by hiring external providers to develop the technology, though only 38% of enterprises have used this method. In-house development or modification of AI systems is much less common (about one in five enterprises).

### *Other survey evidence from national official sources*

Other survey evidence from national official sources also covers Denmark, France and Korea (Montagnier P. and Ek I., 2021[15]). The findings from these national surveys are shown in Table 2.1, broken down by size category of firm. The table shows large differences across countries, ranging from a low of just 1.5 % of all firms in Korea in 2017 to 11.4 % in France in 2018. The possible reasons for such large differences are commented on further below. The data in Table 2.1 also coincide with findings from recent OECD work that used a novel statistical approach to analyse the diffusion of AI in firms across ten countries (Calvino and Fontanelli, 2023[16]). This OECD study used an assemblage of micro-data from firm-level surveys across 11 countries to examine the prevalence and impact of AI in different sectors. It found that AI is mostly used in the ICT and Professional Service sectors and is more widespread across large and somewhat younger firms. The study also showed that companies using AI tend to be more successful, especially the larger ones. It pointed out that complementary assets, including ICT skills, high-speed digital infrastructure, and using other digital technologies, are crucial for companies to get the most out of AI.

## Table 2.1. Share of businesses using AI technology in Denmark (2019), France (2018) and Korea (2017-18)

Survey findings from recent years

| Firm size (employees) | Denmark (2019)[1] | France (2018)[2] | Korea (2017)[3, 5] | Korea (2018)[4, 5] |
|---|---|---|---|---|
| All | 6.0 | 11.4 | 1.5 | 2.1 |
| 10-49 | 4.8 | 10.8 | 1.5 | 1.6 |
| Small (20-99) | - | 11.3 | - | - |
| 50-99 | - | 6.7 | 12.3 | - |
| 100-249 | - | 12.1 | 14.3 | - |
| 100-299 | - | 13.1 | - | - |
| Medium (50-249) | - | 13.1 | 1.1 | 3.6 |
| Large (250+) | 23.5 | 20.7 | 5.4 | 13.9 |
| 300+ | - | 23.2 | - | - |

Notes: 1. Statistics Denmark, www.dst.dk/en. 2. INSEE, www.insee.fr. 3. Ministry of Science and ICT, www.msit.go.kr/eng/index.do. 4. Ministry of Science and ICT www.msit.go.kr/eng/index.do. 5. Based on the establishment level, not on the firm level.
Source: Montagnier and Ek, (2021[17]), "AI measurement in ICT usage surveys: A review," OECD Digital Economy Papers 308, OECD Publishing, https://doi.org/10.1787/72cce754-en.

### *Possible reasons why survey results differ across countries*

A need exists to better understand survey comparability across countries. Some surveys have yielded results that appear counter-intuitive and hard to explain in terms other than methodological. Montagnier and Ek (2021[15]) describe possible sources of difference in survey results. These could include, first, the coverage of the surveys, both in terms of the target population (e.g. business units surveyed can be enterprises or establishments) and in terms of industries and the size of firms included in different sample strata. For example, in Korea (see Table 2.1), the unit surveyed was "establishment", not "enterprise". Second, it may be due to differences in the questionnaires, the heterogeneity of AI definitions and the different nature, wordings and scope of the questions.

## Challenges of AI adoption identified in prior studies

Some of the factors behind weak adoption of AI in enterprises include, broadly speaking, a lack of digital readiness, uncertainty about use cases and return on investment (ROI), concerns about access to skills and talent, and concerns about the cost of AI technology.

Kazakova et al. (Kazakova et al., 2020[18]) reported that the most common internal barriers to AI adoption for European companies were: 1) difficulties hiring staff with the right skills (57% of surveyed establishments reporting this as a barrier); 2) cost of adoption (52%); and 3) cost of adapting operational processes (49%). External barriers are less common, but the most reported were: 1) lack of public/external financing (36%); 2) liability for potential damages (33%); and 3) data standardisation (33%). In addition to being the most frequently reported, internal obstacles were the most significant deterrents to adoption. Of the internal obstacles, lack of internal skills, cost of adoption, lack of internal data, and IT infrastructure were considered the most important.

Establishments in the United Kingdom reported fewer barriers to adoption than the European average, and these barriers were more likely to be external (than for the average country in the analysis). Meanwhile, France and Germany reported more barriers than the European average, and for both countries, the share of internal barriers was roughly in line with the European average.

Table 2.2 shows the most frequently reported internal and external barriers for companies in the European Union, as well as for France, Germany, Italy, and the United Kingdom individually (the survey period preceded the departure of the United Kingdom from the European Union). The most common barriers are internal to firms. The most cited barrier in France was the cost of adapting existing processes; the most commonly cited barrier in Germany was the difficulty of hiring staff with the necessary skills (with more than three in four establishments reporting this as a barrier). The most cited barrier in both Italy and the United Kingdom was the cost of adoption (though less than half of establishments in the United Kingdom report this as a barrier).

### Table 2.2. Most common barriers to AI adoption in companies in the European Union and selected countries, 2020

| | Most common internal barrier | Most common external barrier |
|---|---|---|
| European Union | Difficulties hiring staff with the right skills (57%) | Lack of public/external financing (36%) |
| France | Cost of adapting operational processes (59%) | Liability for potential damage caused (51%) |
| Germany | Difficulties hiring staff with the right skills (76%) | Strict standards for data exchange (53%) |
| Italy | Cost of adoption (62%) | Lack of public/external financing (53%) |
| United Kingdom | Cost of adoption (46%) | Strict standards for data exchange (31%) |

Source: Kazakova et al., (2020[18]), European Enterprise Survey on the Use of Technologies Based on Artificial Intelligence, Publications Office of the European Union, Luxembourg, https://data.europa.eu/doi/10.2759/759368.

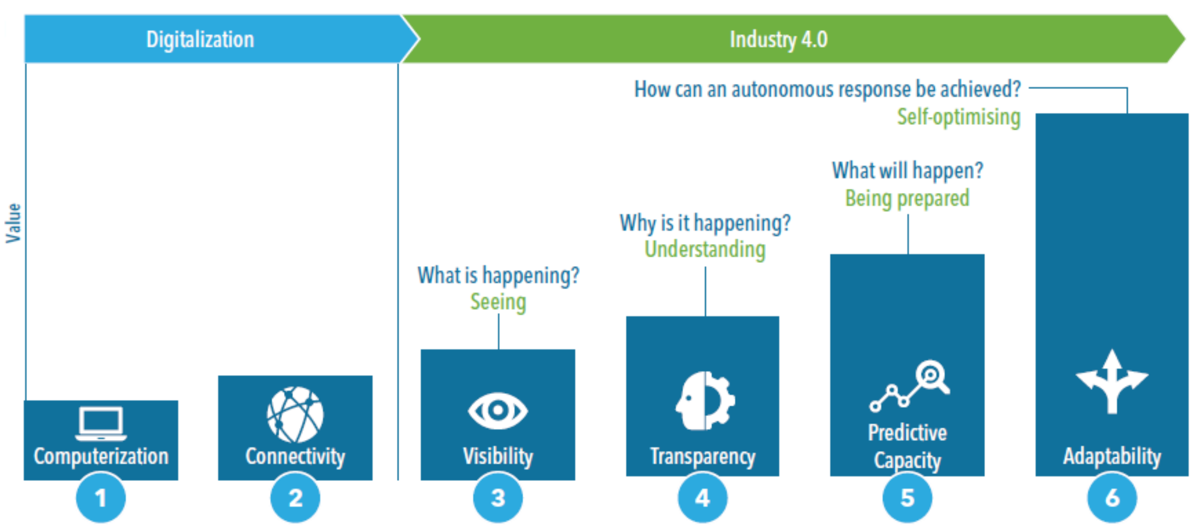
### *Lack of digital readiness*

AI solutions require access to data. However, many firms have not fully digitised key business functions. For example, in the United States, Zolas et al. (2020[6]) find that, overall, “the lowest rates of [digital information] adoption are observed in production and supply chain activities” (although this is impacted by the lower count of manufacturers in their survey). As much as 36% of customer feedback, 38% of information on production activities, and 42% of supply chain-related information is not digitised. These shortfalls restrict the ability to generate value using AI.

Zolas et al. (2020[6]) find that “technology adoption exhibits a hierarchical pattern, with the most sophisticated technologies adopted most often only when more basic applications were as well.” One of the most important technologies many companies will adopt before AI is cloud computing, a platform that makes it easier and cheaper for businesses to innovate with AI by helping them to operate and maintain the IT infrastructure and services they need (Bill Whyman, 2021[19]). However, the ABS found that 60.7% of US companies (including 64.6% of companies in manufacturing industries and 60.6% in non-manufacturing industries) had not yet adopted cloud computing (NSF, 2019[7]).

As shown in Figure 2.9, manufacturers generally progress along six stages of digitalisation (Schuh et al., 2017[20]). Stages 1 and 2 refer to basic digitalisation – “computerisation” and “connectivity” –getting data into computers, integrating companies’ various technology systems, and (for manufacturers) connecting key production equipment into an integrated, enterprise-wide IT system. Companies can then progress to advanced monitoring, being able to see what is happening in real time across the business, from production equipment on the factory floor to parts as they move through the supply chain, customers’ use of a firm’s products and digital services. The firm can possess an always-up-to-date digital model of its factories.

**Figure 2.9. The Industry 4.0 Maturity Index: Stages of digitalisation**

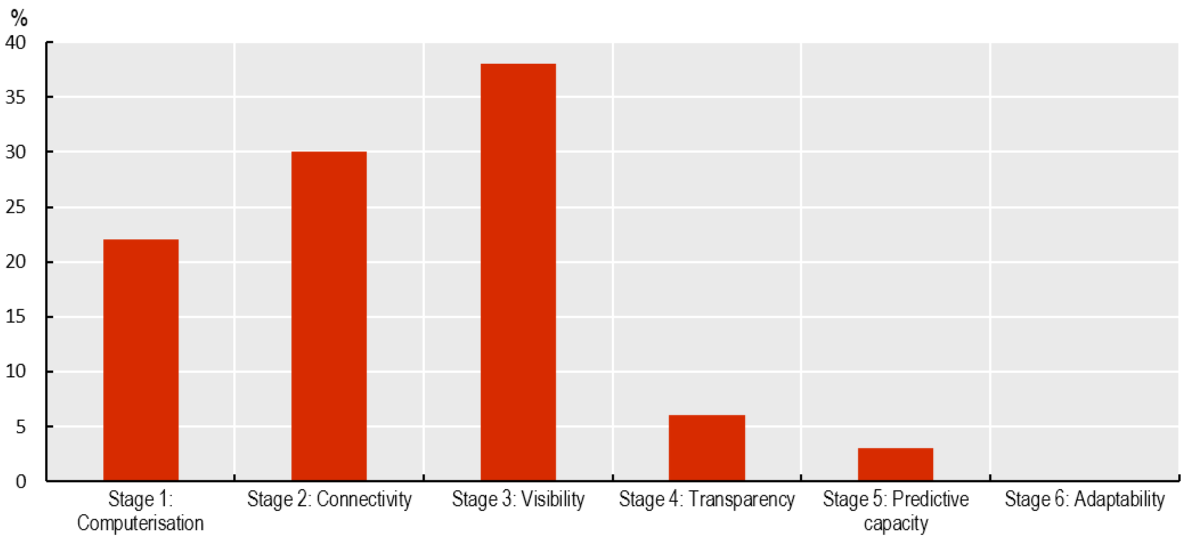



Source: Suchuh et al., (2017[20]), Acatech – National Academy of Science and Engineering, original graphic courtesy FIR e. V. at RWTH Aachen University.

Next, the most sophisticated companies progress to using technologies that permit an understanding of why what is happening is happening. For example, for a manufacturer, this might entail using AI to facilitate root-cause analysis for the failure of a part or a piece of production equipment. Lastly, companies can move to a phase of “Predictive Capacity,” or of being prepared for what may happen (e.g. predicting machine failure in advance or proactively readjusting the flow of inventory to stores) and then, ideally, to “Adaptability,” which refers to self-optimising organisations or factories in which autonomous responses can be achieved, all the way to machines capable of detecting and even fixing their own error modes.

From March to June 2019, the Manufacturers Alliance for Productivity and Innovation (MAPI, now renamed as the Manufacturers Alliance) and the Information Technology and Innovation Foundation (ITIF) surveyed 200 US manufacturers (generally with sales of between USD 500 million and USD 10 billion), receiving 60 usable results (Atkinson and Ezell, 2019[21]). This six-stage model described above was used to assess companies' progress in digitalising manufacturing. Over half of the respondents indicated their companies were only at the initial stages of digitalisation of manufacturing (see Figure 2.10).

### Figure 2.10. Progress in digitalisation, selected large manufacturers in the United States, 2019




Source: Atkinson R. and Ezell S, (2019[21]), The Manufacturing Evolution: How AI Will Transform Manufacturing and the Workforce of the Future, Information Technology and Innovation Foundation, Washington, DC, https://itif.org/publications/2019/08/06/manufacturing-evolution-how-ai-will-transform-manufacturing-and-workforce.

Around two-fifths of the surveyed firms had progressed to the stage of having strong visibility into their manufacturing operations, while less than 10% had achieved either transparency or predictability in manufacturing operations. No respondents reported being at a stage of self-optimisation. Firms at the initial stage of digitalisation – just integrating their IT systems and data sets – which account for half of medium-sized manufacturers in the United States, will find it hard to run AI tools like expert or predictive systems.

The National Science Foundation (2019[7]) reported that the most significant factor adversely affecting AI adoption and utilisation was the cost of the technology, with 12.5% of US manufacturers and 7.3% of non-manufacturers reporting that cost was prohibitive. The next most significant factors adversely affecting AI adoption among manufacturers were lack of capital (2.8%), concerns regarding the technology's maturity, and lack of access to talent (2.4% of respondents each). For non-manufacturers, apart from cost, concerns about the technology's maturity (2.0%) and lack of access to capital (1.4%) were the most important. Overall, 45.9% of respondents reported that AI was not applicable to their business, while 42.4% reported that no factors adversely impacted their adoption of AI.

Enterprises responding to the MAPI/ITIF survey reported that the most significant barrier to deploying AI solutions was a lack of data resources (58% of respondents). The second-most significant barrier was uncertainty about how to use AI solutions to solve specific manufacturing challenges (52%). The third most important barrier was a lack of interoperability between equipment, which precluded the data integration necessary to support AI applications (47%). Other significant concerns included a lack of workplace digital skills, uncertainty about the ROI, and a lack of buy-in from senior executives (see Figure 2.11).

**Figure 2.11. Most significant barriers to US manufacturers' AI adoption, 2019**

Percentage of respondents


Source: Atkinson R. and Ezell S, (2019[21]), The Manufacturing Evolution: How AI Will Transform Manufacturing and the Workforce of the Future, Information Technology and Innovation Foundation, Washington, DC, https://itif.org/publications/2019/08/06/manufacturing-evolution-how-ai-will-transform-manufacturing-and-workforce.

In December 2019, the tech research and outreach company O'Reilly Media surveyed nearly 1 400 business leaders worldwide, with most responses gathered from North America, followed by Western Europe and Asia. It found that the primary reasons businesses choose not to adopt AI were that: 1) "Company culture does not yet recognise needs for AI"; 2) "Difficulties in identifying appropriate business use cases"; 3) "Lack of skilled people/difficulty hiring the required roles"; and 4) "Lack of data or data quality issues" (Magoulas and Swoyer, 2020[22]).

### *Lack of organisational readiness*

Beyond technological costs, what surfaces from the studies cited above is that many firms are uncertain about how to deploy AI tools and what the ROI of using AI might be. Lack of senior management buy-in in many companies also appears problematic. Successfully adopting AI will sometimes require enterprises to develop effective internal change management strategies. For those that do, the rewards could be significant. For instance, one study of companies with revenues over USD 3 billion found that organisations that take steps to embrace digital transformation generate an average of USD 100 million more in operating income each year than those that do not (Arkan, 2018[23]). Yet despite such potential gains, many executives fail to pursue digital transformation projects, partly due to challenges in changing corporate culture or adopting new ways of working. Overcoming such challenges will be vital to capturing the promise of AI.

This highlights a key point made by Daugherty and Wilson (2018[24]) that the enterprises that will do best in gaining from AI are not those that merely apply AI tools to existing processes but the ones that apply AI tools to fully reimagine and reinvent their processes, especially as concerns the creation of collaborative teams of humans working alongside machines. For instance, BMW (Bayerische Motoren Werke AG) determined that human-robot interactions in an automotive factory are about 85% more productive than either humans or robots working on their own (Knight, 2014[25]). As Markus Schaefer, head of production planning at Mercedes-Benz, observed, "When we have people and machines co-operating, such as a person guiding a part-automatic robot, we're much more flexible and can produce many products on one production line. The variety is too much for the machines to take on." (Knight, 2014[25]).

For companies, this leads to another essential point: implementing AI requires effective change management practices. However, a 2019 McKinsey study found that "only 8% of firms engage in core practices that support widespread AI adoption" (Fountaine, McCarthy and Saleh, 2019[26]). The MAPI/ITIF survey queried executives in medium-sized manufacturers on specific change management strategies to enable AI transformation. It found that, among other things, only 8% of respondents had "developed internal retraining programs to upskill existing workers with needed AI/other digital skills." Furthermore, only 8% had "developed a communications process to explain the implications of AI applications and solutions to employees, customers, and partners."

### *Lack of access to skills*

Surveys assessing barriers to AI adoption often find concerns about the availability of human capital, especially the ability of existing workers to adapt to make effective use of AI tools and systems. For instance, a survey of 1 200 C-level executives found that only 25% considered their workforce ready for AI adoption (Shook and Knickrehm, 2019[27]). However, surprisingly, only 3% reported that their organisations had plans to significantly increase investment in training programmes over the next three years. One possible explanation may be that employees are more ready for the AI transformation than their employers think. In fact, 68% of highly skilled workers and nearly half of lower-skilled workers were enthusiastic about AI's potential impact on their work, while 67% of workers considered it important to develop their own skills to work with intelligent machines. As AI becomes more prevalent, investing in people becomes more important (Atkinson and Ezell, 2019[21]).

The competition for top-level data or computer scientists (i.e. professionals who code algorithms and develop AI/ML systems, as opposed to workers who would use them) is acute. Dividing US companies into three groups – "seasoned," "skilled," or "starters", based on their number of AI production deployments undertaken – Deloitte found, in a December 2020 survey, that 41% of "seasoned" companies, 47% of "skilled" companies, and 58% of "starter" companies were experiencing "moderate to major" skills gaps in AI (Jarvis, 2020[28]). Similarly, in a 2020 survey of about 1 000 executives, 39% said they were not using AI because of a lack of technical expertise (McKendrick, 2020[29]). Other research focusing on the US AI workforce found that some skill types are scarcer than others, particularly scientists in computer and information research (Gehlhaus and Rahkovsky, 2021[30]).

### *Lack of vendors of AI solutions*

Another factor that could significantly affect AI adoption is the availability of AI provider enterprises. Businesses in different industries may demand unique AI solutions that require specialised expertise from AI vendors. Consequently, even though specific innovation ecosystems may have many high-quality AI service companies, oligopolies or even monopolies can emerge in some industries and particular areas, leading to higher prices and fewer opportunities for businesses to increase productivity and competitiveness. Competition among AI vendors, however, could induce technology providers to maintain high operational quality, lower prices and retain customers, change specialisation and serve previously unaffected industries, and make technology more available to a wide range of markets.

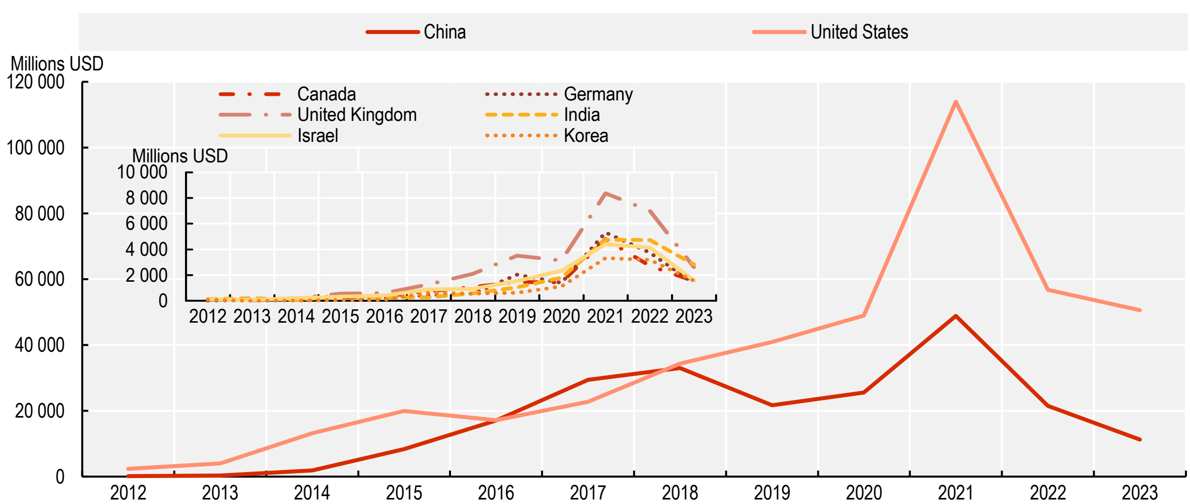
Canada, the United Kingdom, and the United States all have high levels of local competition. According to Statista (2024[31]) (a German company specialising in market and consumer data), there are more than five AI enterprises for every million people in these three countries. Canada has more than seven AI firms per million people. The Canadian performance is perhaps unsurprising as it ranks fourth in the Global AI Index and produced the highest number of AI patents per capita among G7 countries between 2015 and 2018. The European Union is lagging, as dominant countries in the European Union – like France, Germany, and Spain – have fewer than two AI firms per million people. Asian countries face the greatest challenges in terms of the level of AI competition (with India securing only one AI vendor for every ten million people).

VC investment data from CB Insights show that AI vendor firms' participation in VC deals, measured per million of the population, is more than 50% higher in the United States than in Canada (CB Insights, 2021[32]). Europe underperforms the United States and Canada in terms of competition, which hinders the potential to converge on the North American performance. Asia and Latin America considerably lag North America and Europe.

These findings also align with the OECD analysis of global investments by venture capitalists in private companies focused on AI (Tricot, 2021[33]). This work found VC investments in AI to be growing at a dramatic pace. The United States and the People's Republic of China (hereafter, "China") were seen to be leading this wave of investments that tend to concentrate on a few key industries. The data showed that the European Union, the United Kingdom, and Japan increased investments but lagged the two dominant players. The study analysed VC investments in 8 300 AI firms worldwide, covering 20 549 transactions between 2012 and 2020.

Figure 2.12 compares VC investments in AI across several countries from 2012 to an estimated value for 2023. The United States demonstrates a leading position in AI investments, with a noticeable peak in 2018 before continuing the same trendline experienced in prior years. China exhibited a surge in investment in 2017, temporarily surpassing the United States. The EU27 aggregate shows a gradual increase in investment since 2021, reaching levels slightly below those of China in 2022-23. Other countries maintain comparatively low and stable levels of investment throughout the period.

### Figure 2.12. Venture capital investments in AI by country




Note: 2023 value is an estimate.
Source: OECD AI Policy Observatory, https://oecd.ai (accessed on 8 February 2024). Visualisations powered by JSI using data from Preqin.

## Conclusion

AI represents a transformative technology for the 21st century. Countries, industries and enterprises that develop strong competencies in this general-purpose technology will enjoy productivity and competitive advantages. Yet the available survey evidence shows that most enterprises, especially smaller ones, are only at the earliest stages of AI adoption. The literature prior to the OECD (2022-23[34]) indicates that challenges exist in understanding business models and use cases, affording the technology, adopting effective change management practices, and acquiring or retraining skilled workers capable of fully taking advantage of AI technologies.

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## Notes

[1] A PricewaterhouseCoopers (PwC) study found that 52% of surveyed companies accelerated their plans to adopt AI because of the COVID-19 crisis (McKendrick, 2021[35]).

# 3 Key findings from the 2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises

The OECD/Boston Consulting Group/INSEAD study conducted in 2022-23 examines enterprises using artificial intelligence (AI) across the Group of Seven (G7) countries, focusing on the manufacturing and information and communication technology (ICT) services sectors. Novel survey questions address topics relevant to public policy, such as workforce skills and qualifications; types of collaboration with universities and research organisations; barriers to using AI; enterprises’ use of public programmes of financial support; and spending on research and development for AI. Manufacturers, especially small ones, face more adoption obstacles, while larger ICT enterprises invest heavily in employee training and hiring for AI. This chapter also reports on the widespread use of various types of public sector support, as well as enterprises' perspectives on the usefulness of these different support types and the priority they assign to related policy initiatives.

## Summary of main findings

As described in Chapter 1, the OECD/Boston Consulting Group/INSEAD survey conducted in 2022-23 focuses on enterprises using artificial intelligence (AI) and compares relevant characteristics of AI use across the Group of Seven (G7) countries, two economic sectors (manufacturing and information and communications technology [ICT] services), and two enterprise size classes (from 50 to 249 employees and from 250 employees upwards).

The sample sizes are not statistically representative of the population of enterprises in each country. However, the 30-enterprise cell size adheres to widely used statistical norms. Despite the lack of representativeness to national enterprise populations, the findings suggest correlations that other institutions may wish to explore using larger samples. In addition, with a total of 840 enterprises and very few missing data points, rigorous within-sample analysis is feasible.

Relative to previous national and supranational surveys, many of the questions in the survey are novel and of direct policy relevance, such as which types of public support enterprises find useful. All the surveyed enterprises use AI in at least one application, so part of the analysis focuses on the number of AI applications adopted and how this relates to enterprise and industry characteristics. The sample comprises relatively advanced AI users. Consequently, from a policy standpoint, the findings may become increasingly relevant as the number of enterprises seeking to become (advanced) users of AI grows.

A range of possible obstacles to adopting AI were considered – from difficulties in estimating the return on investment (ROI) in AI to lack of external finance. Manufacturers experience all the obstacles more frequently than enterprises in ICT. Small manufacturers are the most likely to experience barriers to adopting AI.

Spending on research and development (R&D) for AI, as a share of all R&D spending, is positively related to how critical enterprises deem AI to be. Perhaps unsurprisingly, enterprises with a higher share of R&D spending going to AI are more likely to establish collaborations on AI with researchers in public research organisations. They also use public training services more often. Performing R&D with the help of AI is also one of the most widespread applications of AI.

Nearly three-quarters of enterprises in both sectors rely on employee training to adopt AI. More than 60% hire new staff to help develop AI technologies. Large enterprises in ICT are the most likely to train employees and hire staff to develop AI technologies. Around 20% of enterprises fail to find suitably qualified candidates when attempting to hire. However, many enterprises also appear to have difficulties fully understanding the skills they need. Most enterprises support developing qualification frameworks for graduates in AI.

Between 51% and 61% of enterprises make use of external data, whether from private data providers (such as organisations dedicated to producing and selling data), from a partner enterprise, or from the public sector.

A significant share of enterprises uses some form of public sector service to aid AI adoption. Most enterprises consider public sector services and initiatives “helpful” or “very helpful”. Enterprises that use more AI applications are more likely to use public support. Perhaps unsurprisingly, large enterprises are less likely to use public support. Enterprises that use AI intensively or face many obstacles to using AI find public services and initiatives more helpful than those that use AI less intensively or experience fewer obstacles. The generally positive view of potential public sector initiatives varies little in terms of industry and firm size.

Both in ICT and manufacturing, the most frequently used services are those that provide access to diverse forms of information or advice. Even in this sample of enterprises, many of which use AI in advanced ways, additional information on various domains of AI is often sought. Initiatives to develop human capital are also among the most widely used and highly valued. Roughly 58% of enterprises make use of training services provided by the public sector. In addition, 42% use programmes that promote access to finance, such as tax credits on R&D spending, grants or credit guarantees.

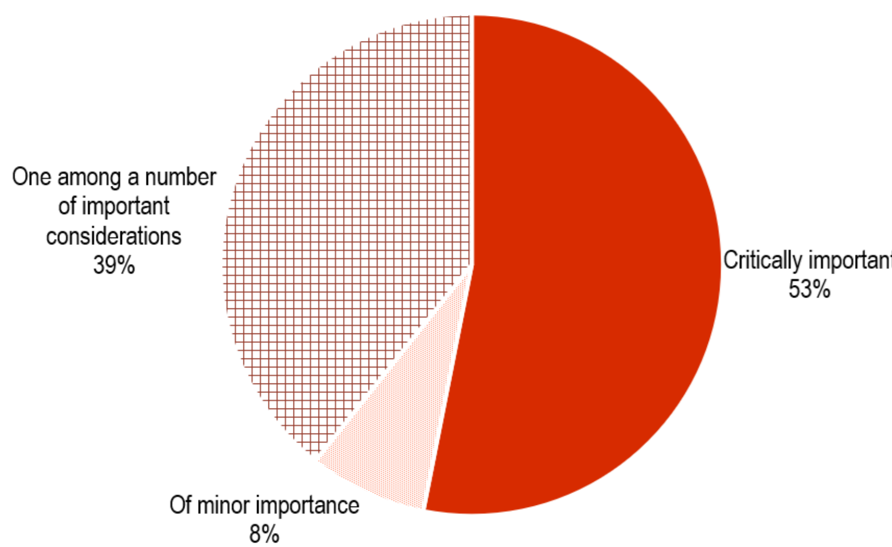
To help adopt and develop AI, many enterprises in the sample collaborate with universities, public research organisations, and other partners. More than half have worked with university faculty, PhD or postdoctoral students over the past 12 months.

The tables in Annex E report the aggregated responses to each survey question.

## Number of uses of AI and their stated importance

All the surveyed enterprises use AI in at least one application. As shown in Figure 3.1, 53% of the sampled enterprises consider AI critically important to their operation. Some 39% hold AI to be one among several important elements in the enterprise, and only 8% view AI as of minor importance.

### Figure 3.1. Importance of AI applications in 840 enterprises across G7 countries, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Because all the sampled enterprises use AI, part of the analysis focuses on what economists refer to as the intensive margin of AI use, i.e. the number of AI applications adopted and how this relates to enterprise and industry characteristics. The intensive margin of AI use has been little studied in the previous literature.

Furthermore, the survey categorises AI applications by the business function they are used for, while in much of the wider literature, AI applications are typically characterised by technology. Examples of business functions are Product Design, Human Resources (HR) and R&D. Examples of AI technologies are speech recognition, image recognition and natural language generation. Each AI technology can be used in many functions. For instance, natural language processing (NLP) can be used for staff recruitment and human resource management, training and cognitive support for workers, customer-facing services and many more. Thus, enterprises may exploit economies of scope associated with AI technologies, using them in several business functions once they are introduced. Indeed, in the current survey, the number of applications enterprises use is higher than found in most other surveys, which may reflect this phenomenon. However, while complementing other studies, direct comparisons are not possible since the set of questions is not identical.

AI can be adopted as a point solution (i.e. solving one specific problem), an application solution or a systems solution. Furthermore, AI used as point solutions can be introduced independently of other functions in an enterprise, and this is typically a first step as enterprises adopt AI. For instance, an enterprise may start using an NLP application to manage customer data, extend its use over time into recommendation systems, and extend further to customer relation management systems, including sales forecasting.

Most of the survey questions have binary answers (e.g. “is not an obstacle/is an obstacle”). The analysis, therefore, applies probit regressions to individual measures or correlates the sum of positive answers to enterprise or industry characteristics. Probit regression is a statistical technique used to estimate the probability of a binary outcome occurring for a population, in this case, a population of AI-using enterprises.

### *Number of uses of AI*

The analysis starts by investigating the number of AI applications each enterprise uses and whether systematic differences exist across countries, industries, and enterprise size. The number of AI applications is the number of “Yes” answers to a screening question presenting the 11 possible applications shown in Table 3.1.

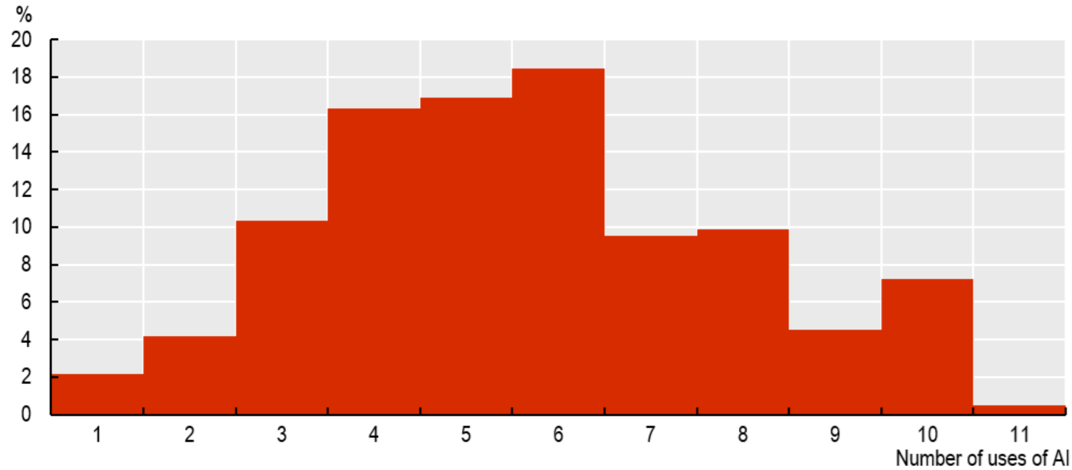
## Table 3.1. The 11 applications of AI considered in the 2022-23 OECD/BCG/INSEAD *Survey of AI-Adopting Enterprises*

| |
|---|
| **Product design,** for instance**,** to generate new designs autonomously or with limited supervision. |
| **Fabrication and assembly**, for instance, using robots and other machine systems that have a high degree of autonomy. |
| **Process control and optimisation**, for instance, to automatically optimise production processes, perform predictive maintenance, or automatically assist programmers. |
| **Detecting defects and anomalies**, for instance, to automate visual inspection of products or to help software developers test and identify defects in code. |
| **Supply chain management**, for instance, for demand forecasting and scheduling optimisation. |
| **Logistics**, for instance, for warehouse automation or delivery optimisation. |
| **Training or cognitive support for workers**, such as systems for enhancing workforce training (using virtual reality) or to support the workforce using augmented reality. |
| **Staff recruitment and/or human resource management**, such as systems that help to select potential recruits based on analysis of past performance of workers with comparable qualifications. |
| **AI to improve research and development (R&D)**, such as machine learning systems to accelerate materials and drug discovery, or experiment with new programming solutions. Such services are often provided by private R&D laboratories. If your enterprise uses such a service, please indicate “yes” in the adjacent column. |
| **Customer-facing services**, for instance, in pricing decisions, to improve the safety of products that are part of the Internet-of-Things (IoT), process data from social media to help predict customer behaviour, or automatically provide users with problem solutions on service desks. |
| Other AI application that is part of core business products or processes. |

Source: OECD authors. *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

The average number of uses across all enterprises is 5.7, and the distribution around the average is slightly skewed towards the right (Figure 3.2). Figure 3.2 can be read as follows: The vertical axis shows the percentage of enterprises adopting the corresponding number of AI applications indicated on the horizontal axis. Thus, about 10% of enterprises use three AI applications, and another 10% use eight AI applications. Or – looking at the horizontal axis – if, for example, the reader is interested in seeing the share of enterprises that uses AI in ten applications, about 7.5 % of the sample is in that category. Given that the sample includes only enterprises that use AI, no enterprises register a zero on the horizontal axis.

**Figure 3.2. Distribution of uses of AI across 840 enterprises in G7 countries, 2022-23**

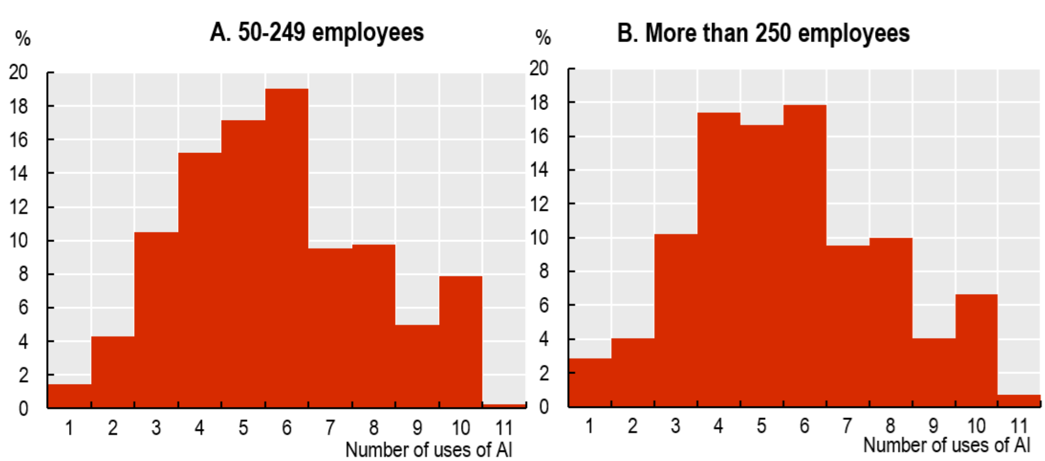



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Of the sample of 840 enterprises, only 4 responded "yes" to using AI in all 11 applications in Table 3.1. Of these, three are in subsectors of ICT: two with their main activity in Data Processing and Hosting Activities, and one in Writing, Testing and Supporting Software. A fourth enterprise operates in Oil and Gas. Three of these four enterprises have more than 250 employees.

Figure 3.3 breaks down the average number of AI uses in relation to enterprise size. The two size categories, in fact, show a very similar pattern. The average number of uses between the size groups is about the same, and so is the skewness. This result is perhaps surprising, as it is well-established that enterprise size is a strong predictor of AI adoption (Bughin et al., 2017[2]; Kinkel, Baumgartner and Cherubini, 2022[3]; Zolas et al., 2020[4]).Considering the average across G7 countries, the OECD Database on ICT Access and Usage by Businesses reports that the share of enterprises using AI is about twice as high in enterprises with more than 250 employees than in enterprises with 50-249 employees (OECD, 2023[5]).

**Figure 3.3. Number of uses of AI by enterprise size across 840 enterprises in G7 countries, 2022-23**

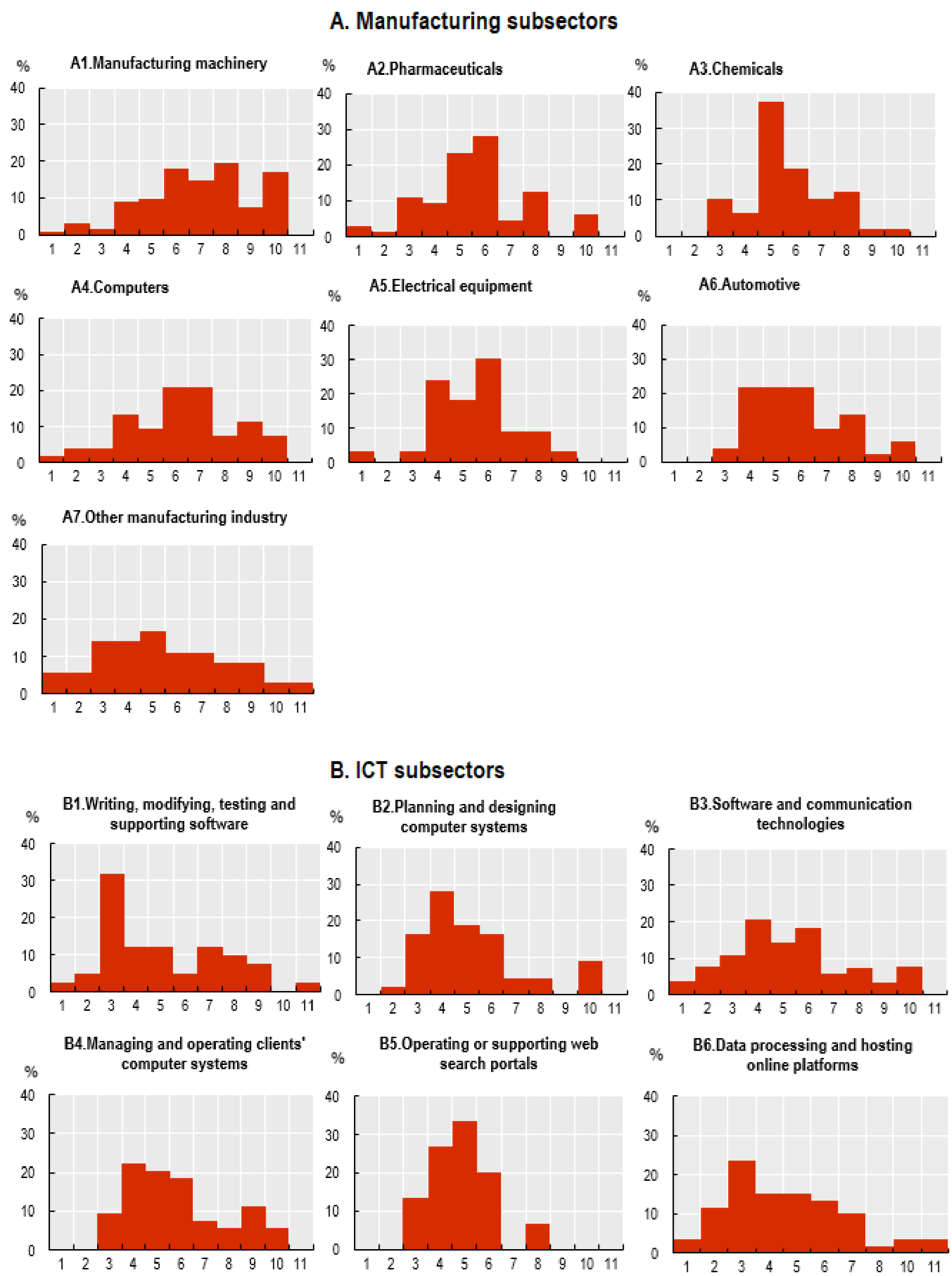



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

However, as previously mentioned, earlier studies mainly focus on AI technologies that can be used in several business functions. A possible explanation for the current and somewhat surprising survey result is that small enterprises are less specialised in their business functions than larger enterprises. Having incurred considerable investment costs to adopt one or more AI technologies, multitasking teams in small and medium-sized enterprises may use them in several functions.

### Figure 3.4. Number of uses of AI by industry subsector across 840 enterprises in G7 countries, 2022-23

Number of AI uses (horizontal axis) and percentage of the sample population of enterprises (vertical axis)

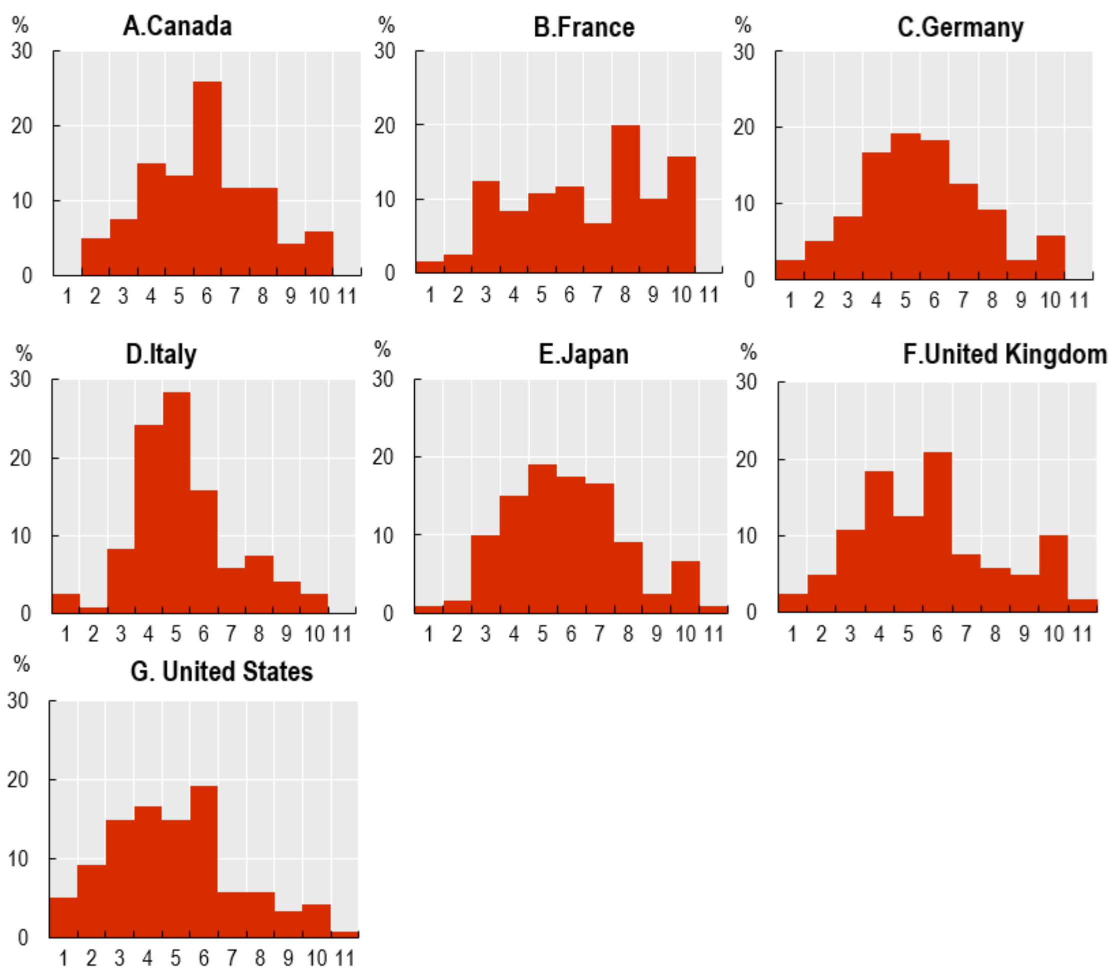



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

The patterns of AI adoption are quite different across industries (Figure 3.4). The highest average number of AI uses is in the subsector of Manufacturing of Machinery. The lowest is in Data Processing and Hosting and Online Platforms. While the former is slightly skewed to the left (that is, with a slight tendency to use fewer applications), the latter is slightly skewed to the right. Managing and Operating Clients' Computer Systems is the industry with the highest skewness, which is skewed to the right. The intensity of AI use by industry largely corresponds with the findings of comprehensive surveys from Sweden (Statistics Sweden, 2021[6]) and the United States (Zolas et al., 2020[4]). However, in Sweden, the highest AI intensity is found in knowledge-intensive business services.

The average number of AI uses also varies across the G7 countries (Figure 3.5). The highest average number of uses (6.4) is in enterprises in France, while the lowest (4.9) is in the United States. The ranking of countries at the intensive margin of AI use is in line with the ranking of the share of enterprises using AI in the OECD Database on ICT Access and Usage by Businesses (OECD, 2023[5]). The results suggest that in countries where the adoption rate of AI is high, enterprises that use AI employ it in more applications. In other words, the extensive and intensive margins are closely related at a country level.

## Figure 3.5. Number of uses of AI across 840 enterprises by G7 country, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Table 3.2 cross-tabulates the average number of AI uses by country and industry using a heat map. The darker shading represents a high average number of AI uses, while lighter shading depicts industry and country combinations with a low average number of AI uses. French enterprises exhibit both the highest and lowest average number of AI uses, respectively, in Manufacturing of Machinery and in Writing, Modifying, Testing, and Supporting Software. The United States stands out with the highest average use of AI in Managing and Operating Clients' Computer Systems.

## Table 3.2. Average number of active AI uses across 840 enterprises by G7 country and industry, 2022-23

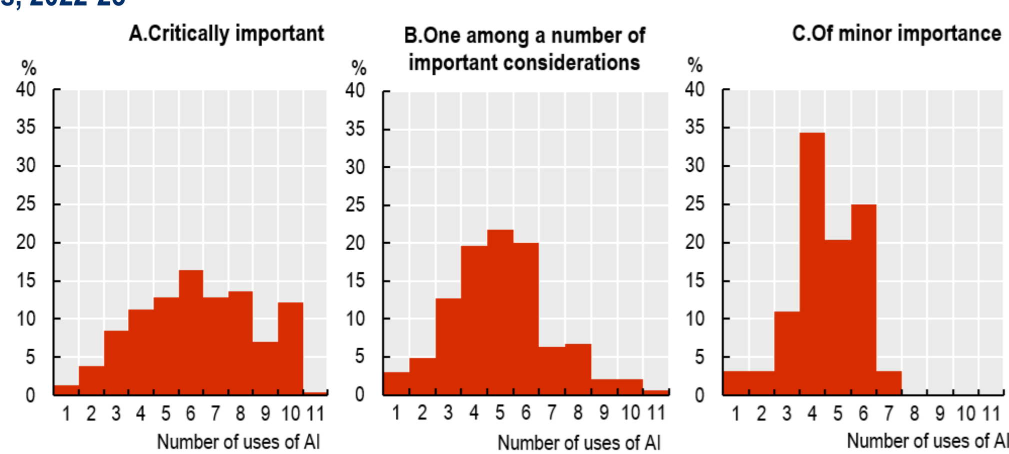
| Industry | Canada | France | Germany | Italy | Japan | United Kingdom | United States |
|---|---|---|---|---|---|---|---|
| Manufacturing machinery | 7.2 | 8.5 | 6.4 | 5.8 | 7.1 | 7.1 | 5.4 |
| Chemicals | 4.8 | 7.7 | 6.0 | 6.1 | 5.3 | 4.8 | 4.0 |
| Pharmaceuticals | 5.5 | 7.8 | 5.0 | 5.6 | 6.0 | 6.0 | 4.6 |
| Automotive | 5.3 | 7.8 | 6.4 | 5.4 | 6.0 | 4.0 | 5.4 |
| Electrical equipment | 6.3 | 5.3 | 5.0 | 4.9 | 6.4 | 4.8 | 6.0 |
| Computers | 6.1 | 8.0 | 4.3 | 6.8 | 6.3 | 6.2 | 5.7 |
| Other manufacturing | 5.5 | 5.8 | 4.2 | 5.2 | 5.6 | 7.0 | 4.5 |
| Writing, modifying, and testing software | 5.8 | 3.0 | 5.0 | 4.0 | 5.3 | 4.8 | 4.9 |
| Planning and designing computer systems | 4.5 | 6.0 | 6.7 | 5.0 | 4.5 | 4.5 | 5.3 |
| Software and communications technologies | 5.6 | 5.5 | 5.5 | 4.6 | 4.9 | 5.6 | 4.6 |
| Managing and operating clients' computer systems | 5.7 | 6.9 | 4.8 | 5.8 | 5.9 | 4.0 | 7.5 |
| Operating or supporting web search portals | 4.7 | 4.3 | 5.5 | 5.0 | 4.0 | 5.5 | |
| Data processing, hosting and online platforms | 4.7 | 3.9 | 4.3 | 4.6 | 5.8 | 4.3 | 5.1 |

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

### *The stated importance of AI*

Figure 3.6 depicts the number of uses of AI by the importance that enterprises give to AI. Enterprises that report that AI is of critical importance (Panel A) also report the highest average number of uses of AI. Enterprises that report that AI is of minor importance (Panel C) have the lowest average number of AI uses. In this latter category, no enterprises use more than seven AI applications.

## Figure 3.6. Number of uses of AI by the reported importance of AI across 840 enterprises in G7 countries, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

### *A closer look at the uses of AI: A probit analysis*

This section studies the conditional probability of enterprises using AI for each of the 11 applications considered. The application "Detecting defects and anomalies" did not pass standard thresholds for goodness of fit and is therefore excluded.

As discussed earlier, the data show no systematic variation in AI use and enterprise size at the aggregate level. However, looking more closely at this finding, but by application, it turns out that for 3 of the 11 applications, there is a significant relationship between AI use and enterprise size. Table 3.3 reports the probit coefficient on enterprise size and the associated predicted probability of AI use for medium-sized and large enterprises, respectively. Enterprise size is positively related to the use of AI in R&D and in a residual open category of "Other core use". By contrast, enterprise size is negatively related to the use of AI in Product Design (hence the negative sign on the probit coefficient).

#### Table 3.3. Enterprise size and the probability of adopting an AI application across 840 enterprises in G7 countries, 2022-23

| AI application | | Predicted average probability | |
|---|---|---|---|
| | Probit coefficient on enterprise size | Medium-sized enterprises | Large enterprises |
| Product design | -0.236** | 0.66 | 0.57 |
| R&D | 0.194** | 0.66 | 0.73 |
| Other core use | 0.350* | 0.05 | 0.09 |

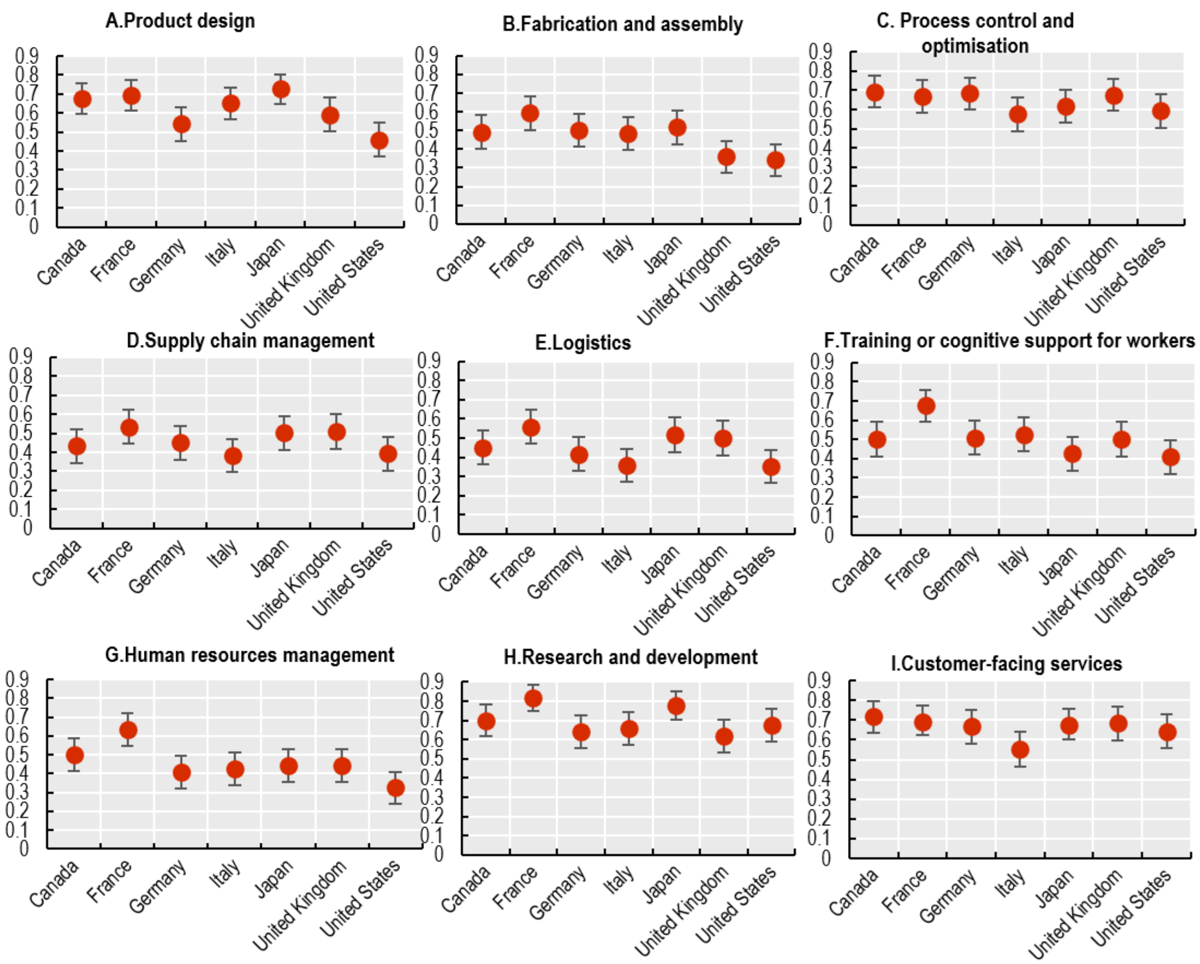
Note: The probit regressions are run with country and industry fixed effects, controlling for enterprise age. There were 840 observations for the applications "Product design" and "R&D" and 512 for "Other core use". The two asterisks (**) and single asterisk (*) signify statistical significance at the 5% and 10% levels, respectively.
Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

The variation in AI adoption by application and country is depicted in Figure 3.7. To understand how to read this figure, take the example of Product Design (upper left chart). The solid dots represent a point estimate of the predicted probability of using AI in Product Design for each country. For example, the average probability that an enterprise will use AI in Product Design in France is 0.7. The band indicated by the thin line shows how precise the estimate is, i.e. the probability that French enterprises adopt AI for Product Design lies between 0.62 and 0.78 with 95% certainty.

Figure 3.7 reveals substantial variation both in applications across the G7 countries and across the applications. French enterprises have the highest probability of using AI in all applications except for Product Design and Customer-facing Services. Japanese enterprises are the most likely to use AI applications in Product Design, while Canadian enterprises are the most frequent users of Customer-facing Services applications. Italy is at the opposite end of the scale, where enterprises are the least likely to use AI applications in Process Control and Optimisation, Supply Chain Management, and Logistics and Customer-facing Services. Enterprises in the United States are the least likely to use AI applications in Product Design and HR, while enterprises in the United Kingdom are the least likely to use AI applications in Fabrication and Assembly and in R&D.

**Figure 3.7. Predictive margins of AI use by application and G7 country, 2022-23**

95% confidence intervals




Note: The figure depicts the predicted probability of using AI in the applications indicated in the heading of each graphic in the figure. The underlying probit regressions control for enterprise size and have industry fixed effects, using robust standard errors.
Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

The survey data also reveal considerable variation in the incidence of AI use both across industries and across applications (variation in the use of AI within applications across industries is presented in Annex F). Across industries, the highest-probability application of AI is R&D. This application also has the smallest variation within and across industries. In other words, the application of AI to R&D is the most likely and consistently used application of AI across enterprises in any given industry and across industries overall.

The industry with the highest probability of AI use is Operating and Supporting the Operation of Web Search Portals. AI is least likely to be used in HR (although AI is widely used in HR in enterprises that specialise in Managing and Operating Clients' Computer Systems and/or Data-processing Facilities). The low frequency of this particular use is perhaps unsurprising, as many enterprises have concerns about inadvertent misapplication of AI in recruitment, a possibility widely acknowledged in public discussion of AI.

### *Enterprise age and the use of AI*

Previous studies have found that enterprise age matters for technology adoption, including AI (Calvino, Criscuolo and Menon, 2016[7]; Haller and Siedschlag, 2011[8]). Older and well-established enterprises may have more resources and experience to absorb the fixed costs of adopting a new technology. However, older enterprises may also face substantial switching costs from old to new technology. Having moved down the average cost curve using their present technology, older enterprises may have less incentive to switch technology than young enterprises and startups that have not incurred the associated sunk costs (Cho et al., 2023[9]); see also Kinkel, Baumgartner and Cherubini (2022[3]) who find that size, R&D and services orientation are important prerequisites for adopting AI in manufacturing enterprises. Which effect dominates is an empirical question.

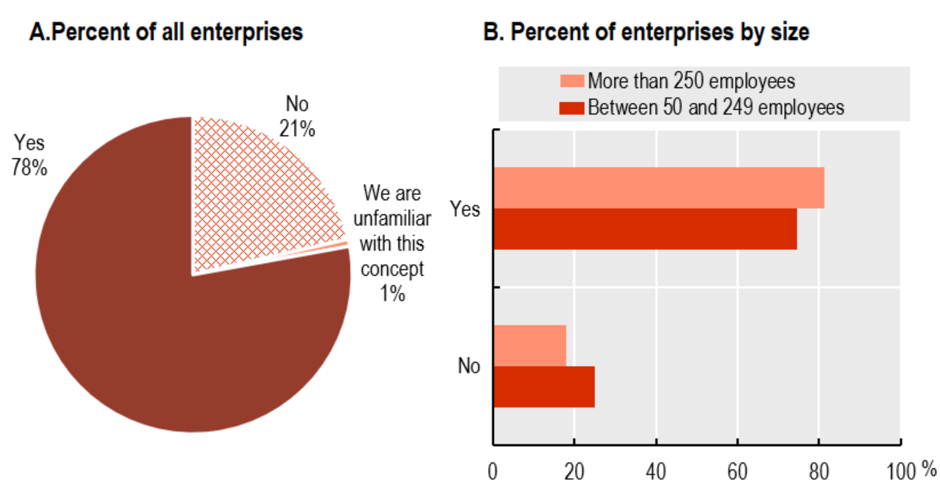
In this connection, Annex G graphs the relationship between AI uptake, age of enterprise and business function, distinguishing between manufacturing and ICT industries. Older enterprises are more likely to use AI in Fabrication and Assembly as well as Logistics, possibly because these are among the most basic functions in manufacturing. Younger enterprises are the most likely to use the remaining AI applications. The difference between old and new enterprises is particularly large in Customer-facing Services and HR. One possibility is that this reflects high switching costs for older enterprises that may have built up large customer services and HR functions.

The survey data show that enterprises in manufacturing and ICT have different patterns of AI adoption. For enterprises of all ages, the probability of adopting AI is higher in manufacturing in traditional manufacturing business functions, including Logistics; Supply Chain Management; Process Control and Optimisation; Fabrication and Assembly, and Product Design. The probability of adoption is higher in services industries in generic functions such as HR; Training and Cognitive Support for Workers; and Customer-facing Services.

## Enterprises and their data sources

Enterprises need access to large quantities of high-quality data to reap the potential benefits of AI. A first point to note is that, overall, the surveyed enterprises were relatively data mature. The literature provides no single measure of data maturity in enterprises, as data can be used in many ways. The survey included a question that would serve as a proxy, namely whether enterprises use a data management solution, such as a data lake.[1]

**Figure 3.8. Use of a data management solution across 840 enterprises in G7 countries, 2022-23**




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Most enterprises in the sample – 78% – use such a solution, and only 1% were unfamiliar with the technology (Figure 3.8, Panel A). Smaller enterprises are a little less likely to use a data management solution (Figure 3.8, Panel B).

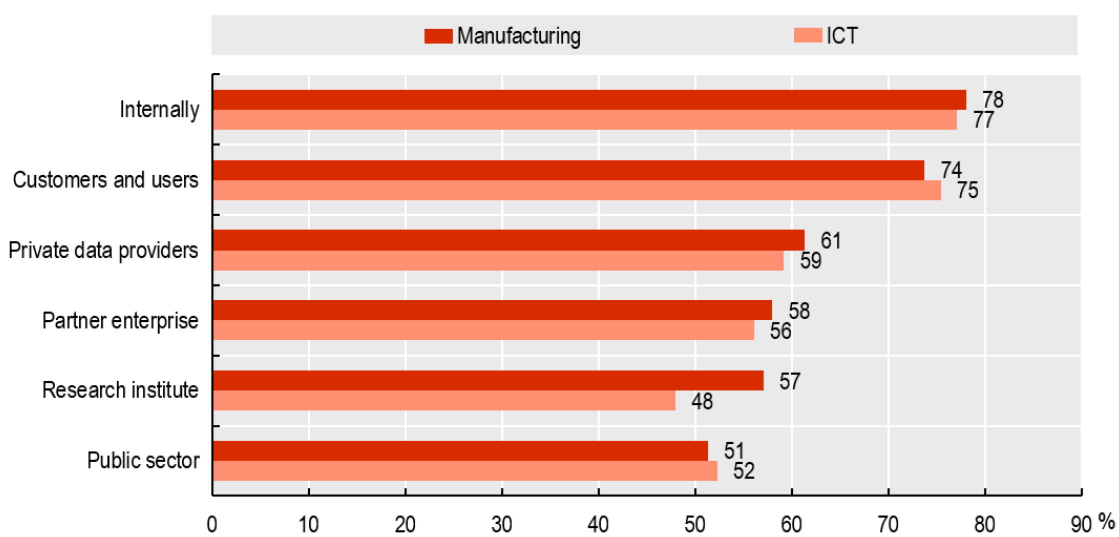
A survey question was also used to gather insights into enterprises' data collection practices. Specifically, enterprises were asked if, during the past 12 months, they had collected or otherwise acquired data from any of the following sources:

- internally from processes and staff
- customers and users
- private data providers, such as organisations dedicated to producing and selling data
- partner enterprises
- research institutes
- the public sector.

Roughly 78% of enterprises in the manufacturing and ICT sectors reported collecting data internally from their own processes and staff (Figure 3.9). With almost the same frequency, enterprises also draw data from customers and users (75%). This source encompasses information gathered from customer interactions, feedback and monitoring of usage patterns, which potentially helps enterprises to enhance customer-centric decision making. The widespread use of these data sources highlights the importance of proprietary data for AI usage and development.

In addition to internal and other proprietary data, access to high-quality external data allows enterprises to supplement their internal data to gain broader analytic insight. The survey shows that between 51% and 61% of enterprises make use of external data, whether from private data providers (such as organisations dedicated to producing and selling data), from a partner enterprise, or from the public sector. Manufacturers are somewhat more likely to use data from research institutes than enterprises in ICT (57% and 48%, respectively).

## Figure 3.9. Sources used by 840 enterprises in G7 countries for collecting or acquiring data, by industry, 2022-23

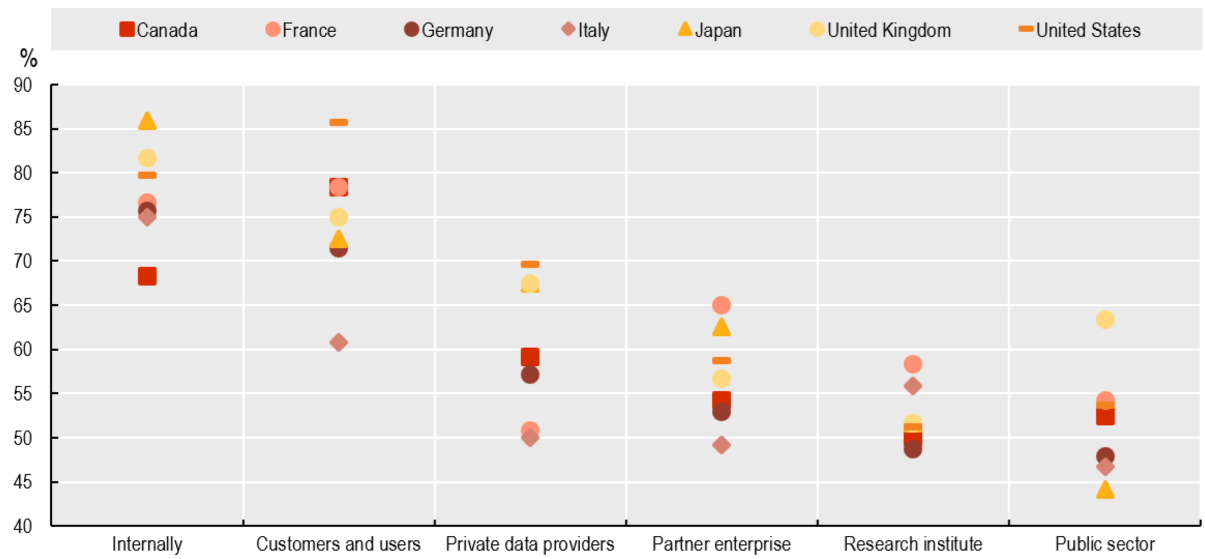



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises.*

The likelihood that any specific data sources are used changes little by size of enterprise. The difference between large and smaller enterprises amounts to less than 10 percentage points for almost all data sources. The exception is for large enterprises in ICT. These are 12 percentage points more likely to use data from public sources than smaller enterprises.

The pattern of use of different data sources differs quite substantially across countries in some instances (Figure 3.10). While 86% of the surveyed enterprises in Japan use internal data, this is only the case for 68% of enterprises in Canada. At the same time, in the United States, most enterprises use data from customers and users as well as private data providers (86% and 70%, respectively). In Italy, this holds for only 60% and 50% of enterprises, respectively. By far the highest incidence of use of data from the public sector is in the United Kingdom (63%).

### Figure 3.10. Sources used by 840 enterprises for collecting or acquiring data, by G7 country, 2022-23



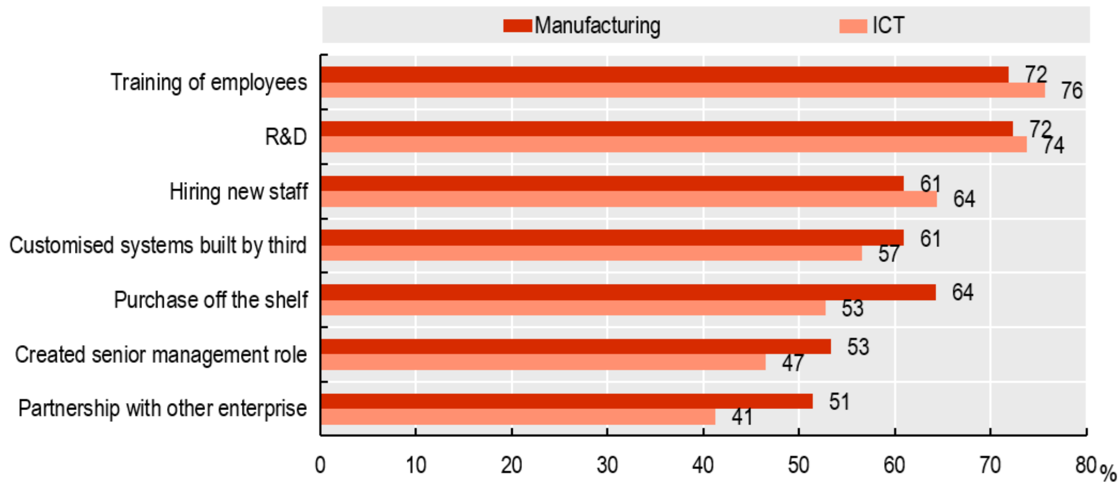

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

## How enterprises adopt and develop AI

Enterprises were asked about the practices they employ to adopt and develop AI. In both sectors, more than 70% report that they carry out R&D on AI technologies for their own use (Figure 3.11). Nearly three-quarters of enterprises in both sectors rely on employee training. In addition, more than 60% hire new staff to further develop AI technologies. Between 53% and 64% of enterprises rely on customised systems built by third parties or purchase off-the-shelf software or hardware. About every second enterprise has institutionalised the development of AI by creating a senior management role or a team with responsibilities for AI. Finally, many enterprises also expedite AI uptake through partnerships with national or international enterprises with capabilities in AI (51% in manufacturing, 41% in ICT).

Large enterprises in ICT are the most likely to train employees (78%) and to hire staff (73%) to develop AI technologies. In contrast, 56% of smaller enterprises in both ICT and manufacturing hire staff for this purpose, compared with 64% of large manufacturers. Consequently, large enterprises in ICT are the least likely to purchase off-the-shelf software or hardware.

### Figure 3.11. Practices to develop AI across 840 enterprises in G7 countries, by industry, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Within the sample, almost 86% of enterprises in the United States carry out some level of R&D to develop AI technologies for their own use. This is considerably higher than in all other countries, with Germany having the second highest share, at 75%. Notably, France has the highest share of enterprises that train their employees, hire new staff, or partner with other enterprises to develop AI.

#### *A deeper look at R&D*

Prior work has shown that investment in R&D relates to the use and development of AI in several ways. Enterprises with more researchers are better placed in terms of skills to adopt, adapt and innovate with AI. A correlation also exists between the use of AI and spending on R&D, given that AI is an increasingly prevalent research tool (Nolan, 2021[10]).

In the survey sample, spending on R&D for AI, as a share of all R&D spending, is positively related to how critical enterprises deem AI to be. Some 38% of enterprises that allocate between 0-10% of their R&D spending to AI consider this technology critically important to their core business processes. By comparison, among enterprises that spend between 11% and 30% of their R&D outlays on AI, 68% consider AI critical to their business. This is the case for 87% of enterprises spending more than 30% (Table 3.4).

### Table 3.4. The intensity of enterprises' spending on R&D for AI across 840 enterprises in G7 countries, 2022-23

Variation by country, enterprise size, industry and criticality of AI to the enterprise

| | Enterprise R&D spending on AI, as a % of total R&D spending | | |
|---|---|---|---|
| | Zero or up to 10% | Between 11% and 30% | More than 30% |
| Number of observations | 439 | 309 | 71 |
| | | | |
| **Observations by country** (values represent a share of all enterprises in each R&D spending category) | | | |
| Canada | 15% | 14% | 13% |
| France | 10% | 18% | 20% |
| Germany | 14% | 14% | 20% |

| | | | |
|---|---|---|---|
| Italy | 16% | 14% | 6% |
| Japan | 12% | 19% | 10% |
| United Kingdom | 16% | 11% | 17% |
| United States | 16% | 10% | 15% |
| **Observations by size and industry** | | | |
| Large manufacturing | 32% | 17% | 7% |
| Medium-sized manufacturing | 23% | 27% | 31% |
| Large ICTs | 24% | 27% | 18% |
| Medium-sized ICTs | 20% | 29% | 44% |
| **Importance of AI applications to the enterprise's core business process** | | | |
| Critically important | 38% | 68% | 87% |

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Enterprises that spend more intensively on R&D for AI also use public training services more often. The survey showed that 65% of enterprises allocating more than 30% of their R&D spending to AI have also used public training services in the past 12 months, compared to 51% of companies with R&D spending on AI of up to 10% of their total outlay on R&D.

Perhaps unsurprisingly, enterprises that spend more of their R&D on AI are more likely to establish collaborations on AI with researchers in public research organisations. Between 60% and 65% of enterprises with R&D spending on AI higher than 11% have such collaborations, compared to 44% of enterprises that spend less than 10%. The importance of R&D in connection with AI is noteworthy for policy makers, who possess various tools for incentivising and giving direction to this form of investment. Educational and research institutions also possess a range of tools to facilitate such investments and collaborations.

### *Collaboration with universities and public research organisations*

Many enterprises in the sample collaborate with universities, public research organisations and other partners to aid the use and development of AI. More than half have worked with university faculty, PhD or postdoctoral students over the past 12 months (Table 3.5). Partnerships with researchers in public research organisations are somewhat more prevalent among manufacturers (55%) than enterprises in ICT (48%). Roughly one-third of all enterprises work with undergraduate students.

In a context where AI skills are almost scarce everywhere, one reason why enterprises collaborate with universities is to secure access to talented graduates. As shown in Table 3.5, a high share (76%) of enterprises collaborating with universities recruited graduates in AI in the previous 12 months.

## Table 3.5. Collaboration with universities and students and graduate recruitment across 840 enterprises in G7 countries, 2022-23

| | **Enterprise has recruited graduates in AI, machine learning or related fields in the past 12 months** | | |
|---|---|---|---|
| **Enterprise has established collaboration to develop AI with university faculty members, PhD or postdoctoral students in the past 12 months** | Yes (n=512) | No (could not hire appropriate candidates) (n=156) | No (did not have specific vacancies) (n=172) |
| Yes (n=468) | **76%** | 15% | 9% |
| No (n=371) | 43% | 23% | 34% |

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

A further indication of the importance of human capital is the high share of enterprises that consider government investment in university education and vocational training related to AI as “very helpful” or “helpful”. Even among enterprises that do not consider AI as central to their core business process, 73% hold that such initiatives are “very helpful” or “helpful” (Table 3.6).

## Table 3.6. Enterprise views on the usefulness of government investment in tertiary and vocational education relevant to AI across 840 enterprises in G7 countries, 2022-23

| | Perceived usefulness of government investing in university education and vocational training in fields related to AI (for the enterprise's adoption of AI) | |
|---|---|---|
| **Importance of AI applications to the enterprise's core business process** | Very helpful or helpful (n=685) | A little helpful or not helpful at all (n=155) |
| Critically important (n=445) | **89%** | 11% |
| One among a number of important considerations or of minor importance (n=394) | **73%** | 27% |

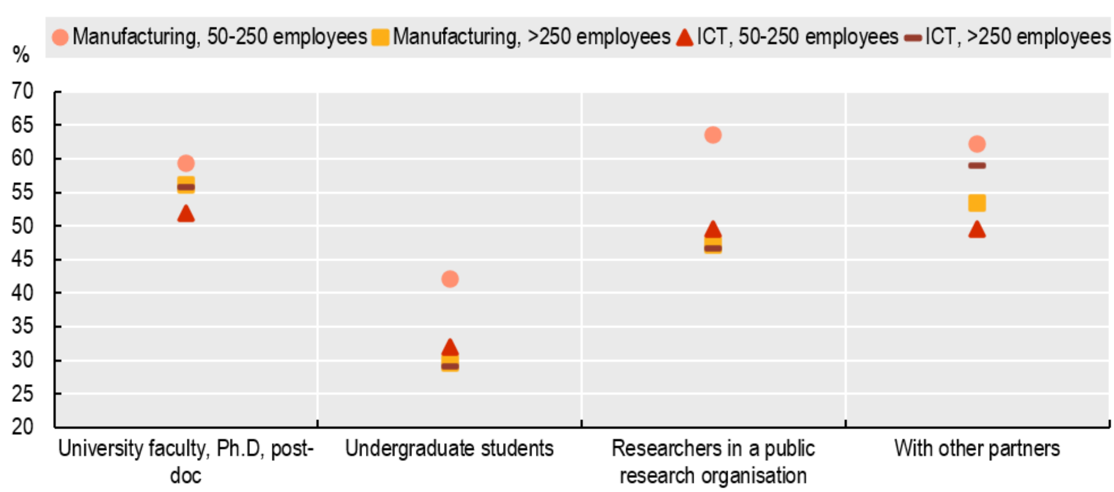
Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Collaborations with researchers in public research organisations are particularly widespread among smaller manufacturers (64%). By contrast, such collaborations were reported by about half of enterprises in other sectors (Figure 3.12).

Enterprises in the United States are less likely than enterprises in other countries to collaborate with university faculty, undergraduate students and researchers in public research organisations (Figure 3.13). However, 60% collaborate with other partners, which is the third-highest incidence in the G7 group.

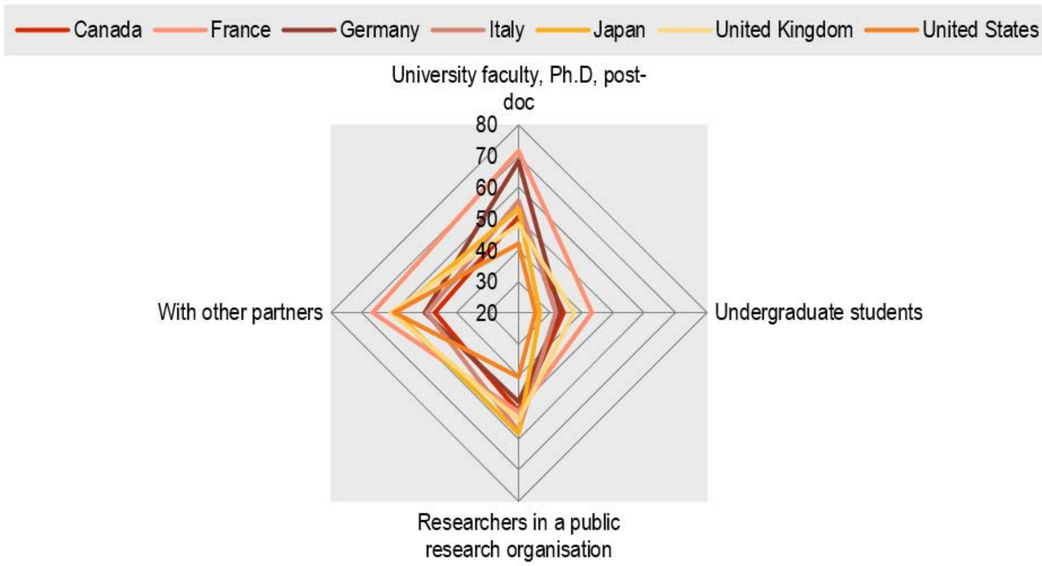
The highest share of enterprises working with other partners to develop AI is observed in France (67%). In addition, France has the highest share of enterprises collaborating with university faculty (72%) and undergraduate students (43%). In the sample, enterprise collaboration with public research organisations is most frequent in Japan (58%).

## Figure 3.12. Collaborations to develop AI, by industry and size, across 840 enterprises in G7 countries, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

### Figure 3.13. Frequency of enterprise collaborations to develop AI by country, 2022-23

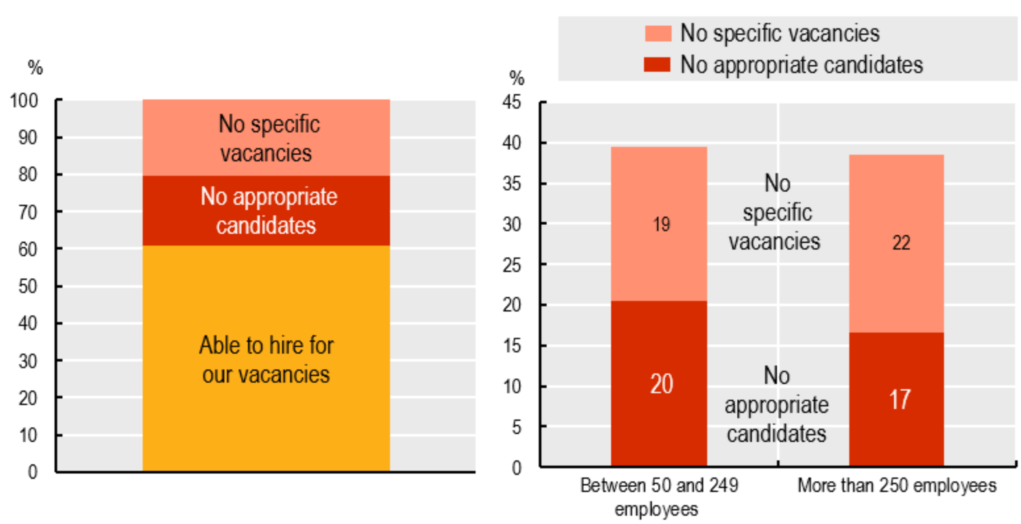



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.Obstacles to using and adopting AI

### *Workforce skills*

In the survey sample, most enterprises had been active in hiring AI skills during the previous 12 months. Indeed, around 60% of enterprises hired employees with AI skills during this period (Figure 3.14). However, an almost universal finding from studies internationally is that a shortage of workforce skills presents a main bottleneck for firms seeking to implement AI. The current survey echoes those findings. Around 20% of enterprises with 50-250 employees report being unable to find appropriately qualified candidates for available vacancies. Even many large enterprises – approximately 17% – experience the same problem.

### Figure 3.14. Enterprises' recent experience of hiring for AI by enterprise size, across 840 enterprises in G7 countries, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

*Do enterprises understand which skills they need?*

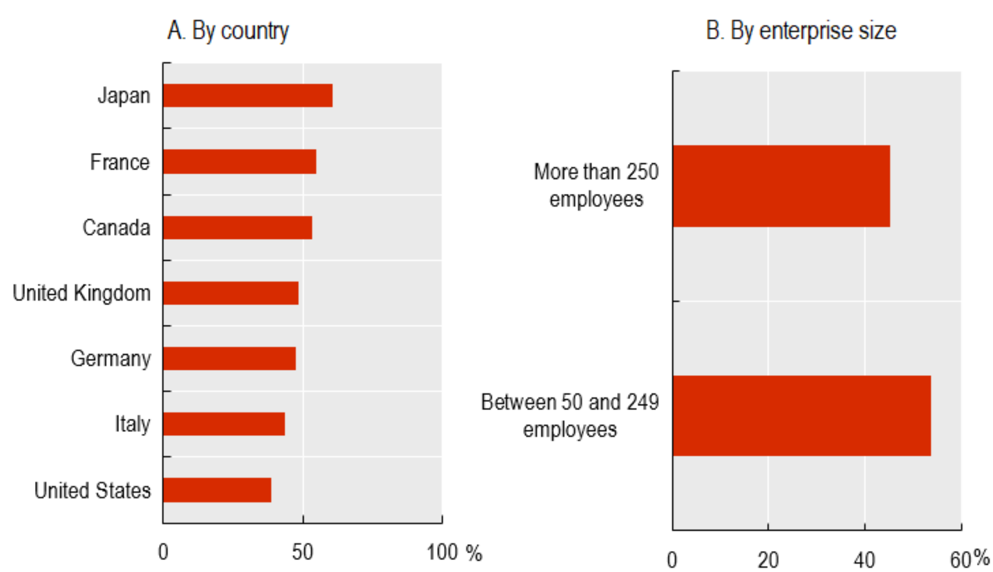
A less-frequently addressed question is whether firms fully understand their skills needs and whether formal academic qualifications provide sufficient information to employers making recruitment decisions. There are several reasons why fully understanding skills needs in AI might be a problem for some enterprises. “AI” is, in fact, an umbrella term encompassing many subdisciplines. Firms in sectors without a tradition of data analytics or small firms that do not have the in-house expertise to make the necessary technical distinctions might lack a strong basis on which to search for skills. In addition, AI technologies are changing quickly, complicating the assessment of job seekers’ suitability.

To explore this topic, the survey asked if enterprises had experienced difficulties during the preceding 12 months in understanding what skill sets to look for in potential AI recruits. Almost 19% of respondents had experienced this problem (Figure 3.15). This number varies somewhat by enterprise size, affecting around 20% of smaller enterprises but less than 17% of enterprises with more than 250 employees. This finding has several possible implications for policy, especially concerning the possible development of new qualifications frameworks.

A large majority (86%) of enterprises that highly value support for partnerships with educational and vocational institutions also consider the development of new qualification frameworks to be either “very useful” or “moderately useful” (

Table 3.7). In other words, many enterprises interested in or searching for increased AI skills also feel they need a better practical understanding of how to identify and use the necessary skills.

### Figure 3.15. Share of 840 enterprises in G7 countries that report difficulties in understanding the skills needed in new AI recruits, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises.*

### Table 3.7. The perceived usefulness of public support for education and training partnerships and the development of qualification frameworks across 840 enterprises in G7 countries, 2022-23

| | Perceived usefulness of support to develop qualification frameworks for graduates in the field of AI | |
|---|---|---|
| **Perceived usefulness of public support for partnerships with educational and vocational institutions as a means to strengthen staff skills in AI** | Very useful or moderately useful (n=684) | Slightly useful or not useful at all (n=156) |
| Very useful or moderately useful (n=706) | 86% | 14% |
| Slightly useful or not useful at all (n=134) | 57% | 43% |

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

### *Other obstacles to using AI*

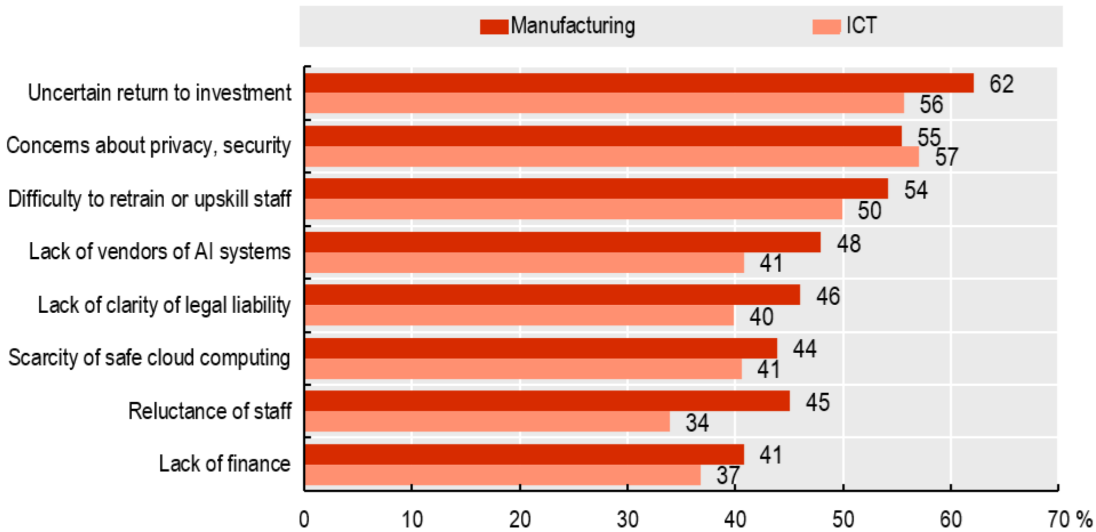
Respondents were asked to indicate which, if any, of 8 conditions had limited the enterprise in implementing AI applications in the preceding 12 months. The options presented were:

1. difficulties in estimating the returns on investment in AI applications
2. concerns related to data privacy, data protection or data security
3. scarcity of cloud computing solutions that guarantee data security and regulatory compliance
4. lack of clarity about the legal consequences in case of damage caused by using AI
5. lack of vendors of AI systems offering solutions tailored to the enterprise's needs
6. lack of external finance for investment to support AI adoption
7. reluctance of staff to adopt AI
8. difficulties in retraining or upskilling staff.

Manufacturers experience all the above obstacles more frequently than enterprises in ICT. This might have several causes. For example, manufacturing has always been product rather than data-led and has less of a tradition of working with big data (although differences exist within manufacturing, especially as regards continuous flow manufacturing; for instance, of petrochemicals and manufacturing of discrete products, such as cars). There is only one exception to this higher incidence of obstacles experienced by manufacturers, namely concerns related to data privacy, data protection or data security (Figure 3.16). Some 55% of manufacturers and 57% of enterprises in ICT report that these concerns have limited their use of AI in the past 12 months. The comparatively high frequency of concerns among manufacturers about data privacy might be somewhat surprising in that manufacturers generally gather less confidential data than do many enterprises in ICT. However, worries over data security rather than data privacy may be the primary concern here for manufacturers.

**Figure 3.16. Obstacles to adopting AI across 840 enterprises in G7 countries, by industry, 2022-23**

Percentage of all enterprises stating the issue to be a concern




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

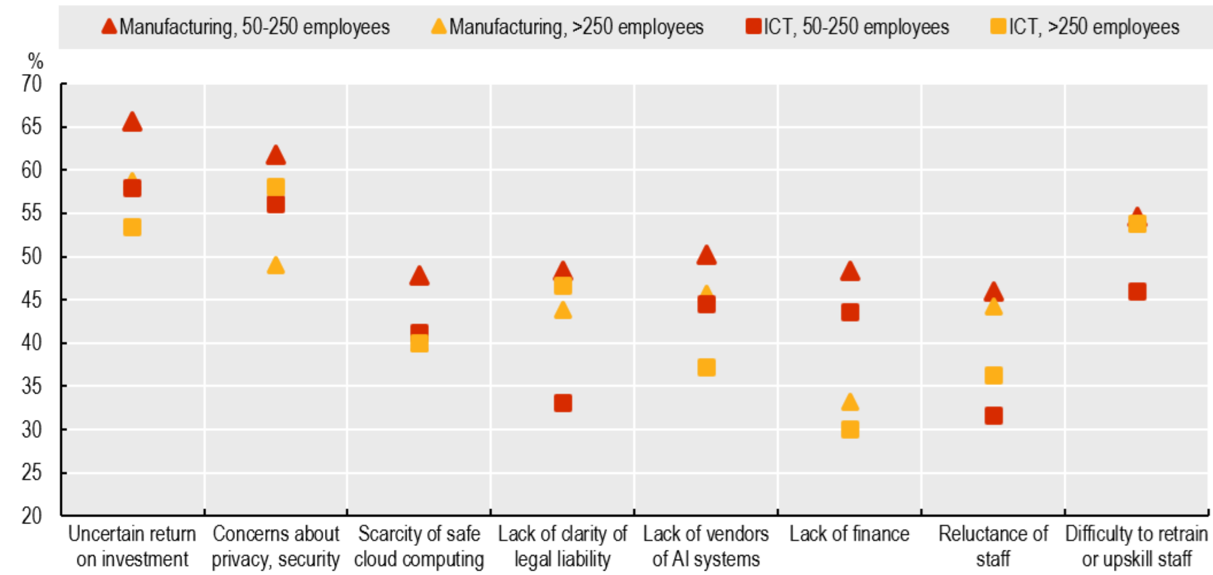
The most frequently experienced obstacle is the difficulty in estimating *a priori* the ROI in AI applications. Some 62% of manufacturers and 56% of enterprises in ICT cite this as problematic. This result echoes findings from many previous surveys, as well as the experience of agencies across the G7 countries charged with accelerating the spread of digital technologies in firms (see Chapter 4). Part of the reason for uncertainty around the ROI is that many AI projects involve a degree of experimentation, with no guarantee of success. In addition, the key processes of data cleaning and model development involve an element of art. Compounding these uncertainties, investment decisions might also have to include complex strategic considerations, such as the need for the firm to remain viable in future supply chains.

More than 40% of enterprises in both manufacturing and ICT cite challenges in finding AI system vendors that offer solutions tailored to their needs. This observation, noted in other work, has motivated some public sector agencies – for instance, in Singapore – to signpost vendors with suitable track records, with the aim of lowering search costs, especially for small firms.

Around 40% of enterprises also report that they encounter a lack of clarity around the legal consequences of damages caused by AI, as well as a scarcity of cloud computing solutions that guarantee data security and regulatory compliance (see the following section on cloud computing). Approximately 40% of enterprises affirm that a lack of external finance for investment to support AI adoption limited the use of AI in the past 12 months. However, again, this result is sensitive to enterprise size: larger enterprises are considerably less likely to report such financial barriers (33% in manufacturing and 30% in ICT). This finding might be explained by the fact that smaller enterprises generally possess less capital to invest, as well as greater constraints linked to cash flow, which are especially important limitations when investment returns are relatively uncertain. In such circumstances, externally provided subsidies are much sought after.

Small manufacturers are more likely to experience barriers to adopting AI than any of the remaining groups of enterprises (Figure 3.17). For instance, while about 50% of smaller manufacturers find it hard to identify vendors of AI solutions tailored to their needs, this is true for only 37% of large enterprises in ICT.

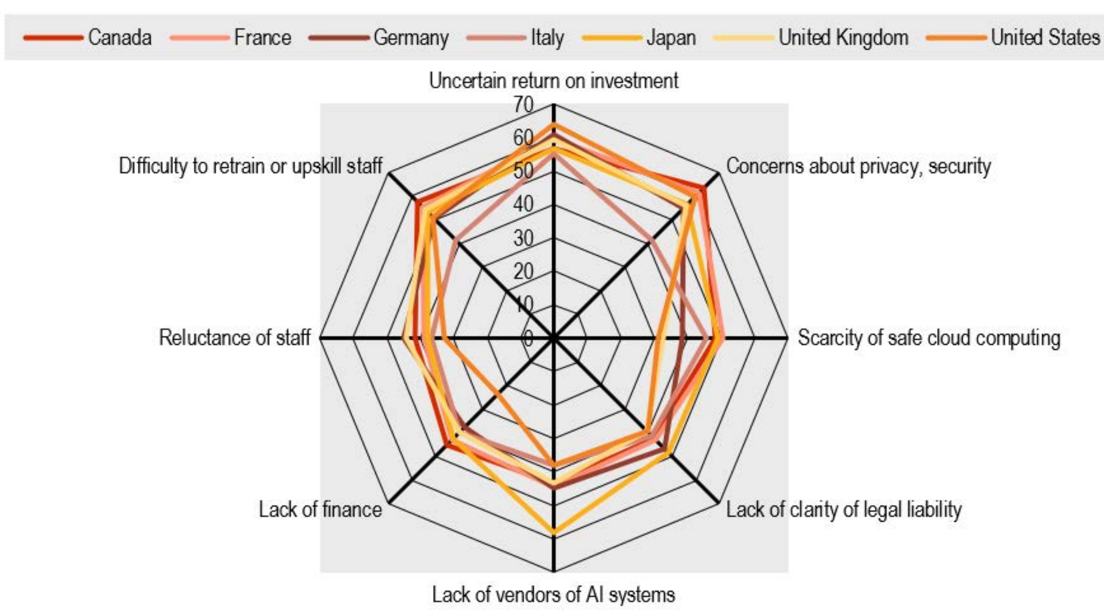
## Figure 3.17. Obstacles to adopting AI, by industry and enterprise size, across 840 enterprises in G7 countries, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Enterprises in the United States are the least likely to report problems for five out of the eight cited obstacles to AI adoption (Figure 3.18). The most pronounced difference between the United States and other countries is in external finance to support the uptake of AI. Only 24% of enterprises in the United States consider this a problem, compared with 38% in Germany. At 45%, Canada has the highest share of enterprises that cite external finance as a challenge.

## Figure 3.18. Obstacles to the adoption of AI across 840 enterprises, by G7 country, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Roughly every second enterprise reports difficulties in retraining or upskilling staff, a finding which might be amenable to change through education and training policies. A further challenge is the apparent reluctance of some staff to retrain or upskill, as cited by 45% of manufacturers and 34% of enterprises in ICT.

### *Obstacles to using cloud computing*

Previous studies on AI adoption have found a hierarchy of technology adoption where early users of websites and computer systems are also early users of cloud services, followed then by AI use (Zolas et al., 2020[4]).

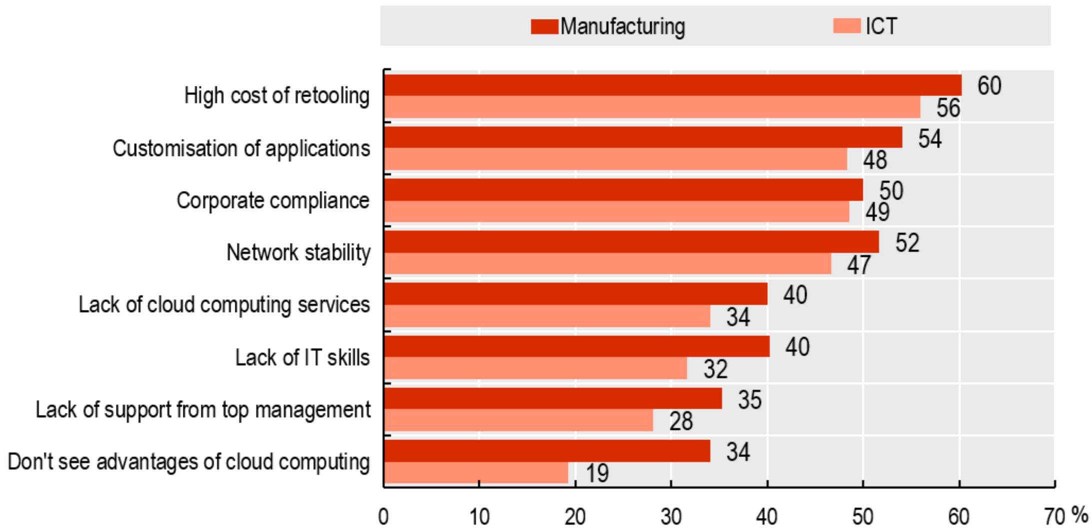
A significant share of enterprises reports challenges in using cloud computing. This matters because of the complementarity between cloud computing and many AI applications. For instance, Industry 4.0 requires increased data sharing across production sites and company boundaries. Leading edge manufacturers may wish to know the real-time status of production equipment in companies that produce key components for their products. Increasingly, machine data and data analytics, and even monitoring and control systems, will operate in the cloud. However, it is already known from previous studies that cloud use varies significantly between small and large firms, and across countries. For example, in 2021, in Finland, around 99% of firms with 250 or more employees purchased cloud services. By comparison, in Japan, in 2019 (the latest year for which data are available), only 49% of firms of the same size used cloud services. The OECD and EU averages were 74% (2022) and 72% (2021), respectively (OECD, 2023[11]).

While many surveys have collected data on enterprise use of cloud computing, few have explored the reasons for non- or problematic use. The current survey does not directly ask questions about previous use of cloud services. However, the respondents were asked to indicate what kind of obstacles they encountered when using cloud services. The obstacles considered in the survey were the following:

- high cost of retooling systems
- concerns about corporate compliance
- concerns about customisation of applications
- concerns about network stability
- lack of availability of adequate cloud computing services
- do not see the advantages of cloud computing
- lack of support from top management
- lack of IT skills.

The cost of retooling systems is the most frequently cited obstacle to using cloud computing, both in manufacturing (60%) and ICT (56%) (Figure 3.19). Approximately every second enterprise in both sectors has concerns about customisation of applications, corporate compliance, or network stability. Roughly one-third report that a lack of IT skills – for instance, in cloud engineering – limits their use of cloud computing. Finally, and somewhat surprisingly, a substantial share of enterprises in manufacturing (34%) state that they do not see advantages in cloud computing.

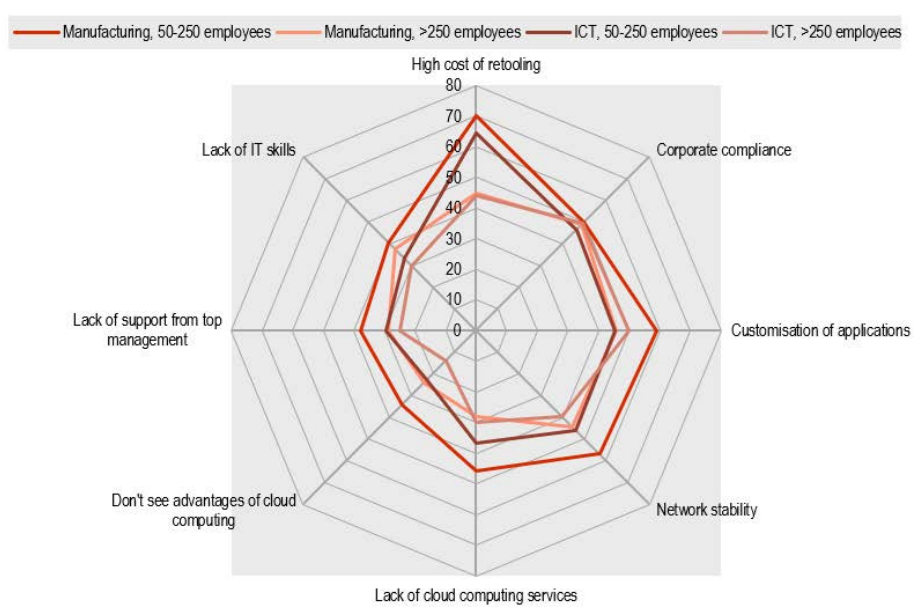
## Figure 3.19. Obstacles to the use of cloud computing by industry across 840 enterprises in G7 countries, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Manufacturers – especially smaller manufacturers – are more likely to report obstacles than enterprises in ICT (Figure 3.20). Nevertheless, the ranking of the various obstacles is similar across both sectors. The importance of enterprise size is particularly pronounced when it comes to cost constraints on retooling systems. While nearly 70% of enterprises with 50 to 250 employees indicate that the cost of retooling limits their use of cloud computing, this is true for only 44% of enterprises with more than 250 employees.

## Figure 3.20. Obstacles to the use of cloud computing by industry and enterprise size, across 840 enterprises in G7 countries, 2022-23

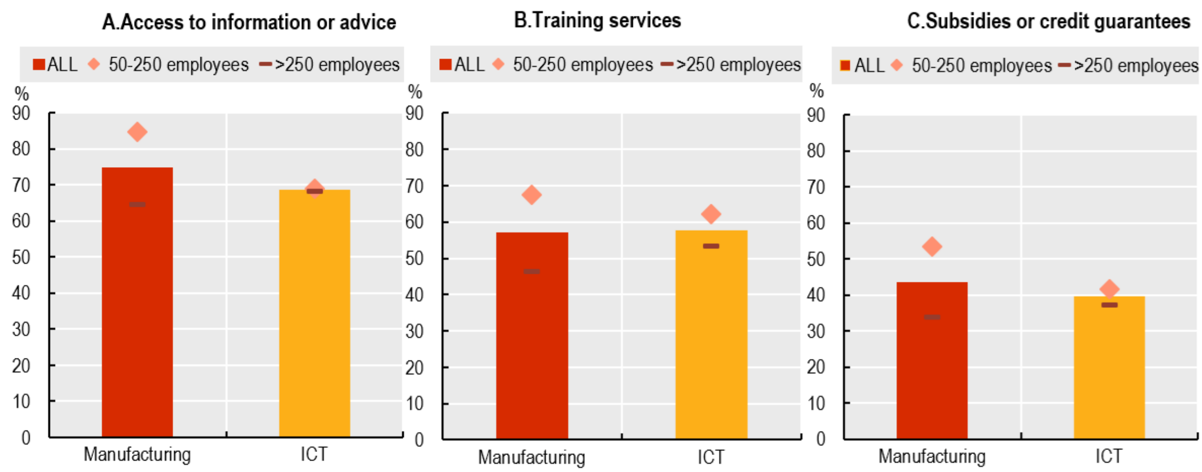



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

## Public services to support the adoption of AI

A salient feature of the survey – not examined in previous studies – is an assessment of the extent to which enterprises use public sector services to support the adoption of AI (Figure 3.21).

### Figure 3.21. Use of public services supporting the adoption of AI across 840 enterprises in G7 countries, by industry, 2022-23



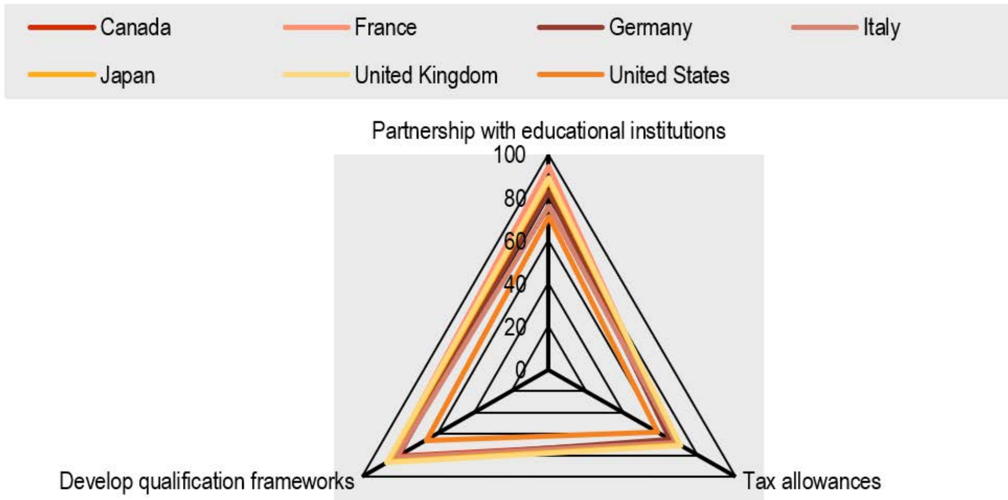

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Foremost among the survey findings is that a significant share of enterprises uses such services. The most frequently used services in ICT and manufacturing are those that provide access to information or advice (75% in manufacturing, 69% in ICT). Roughly 58% of enterprises make use of training services provided by the public sector, and around 42% use programmes that promote access to finance, such as tax credits on R&D spending, grants, or credit guarantees.

Public sector services are used most by manufacturers with 50 to 250 employees. For instance, 85% of such enterprises use information or advisory services, compared with roughly 68% for other groups of enterprises.

Among the surveyed countries, enterprises in Japan are the most frequent users of public sector services to assist in using AI (Figure 3.22). This is particularly so for services that provide information or advice (82%). The differences between Japan and other countries are less pronounced for other service types.

**Figure 3.22. Public services used to support the adoption of AI across 840 enterprises, by G7 country, 2022-23**




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Enterprises in the United States are much less likely to use public sector services than enterprises in other countries. For instance, only 19% of enterprises in the United States use services that promote access to finance, as compared with 50% of enterprises in Japan.

### *Supporting growth in workforce skills in AI*

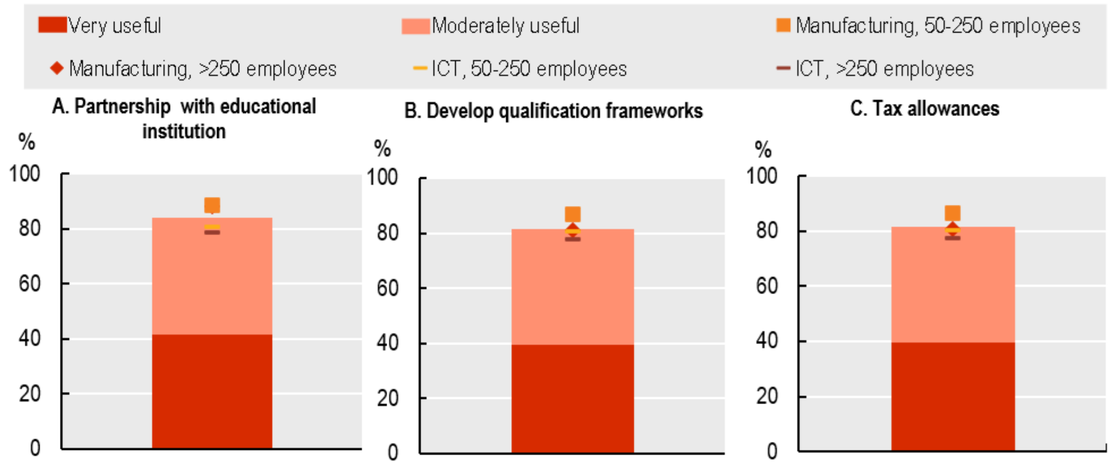
Firms can increase the skills of their workforce in a variety of ways. Enterprises were asked about the usefulness of three support mechanisms, all of which are amenable to change by policy makers. Specifically, enterprises were queried on how helpful the following types of support could be to increase staff skills in AI:

- partnerships with educational and vocational institutions
- tax allowances or tax credits for training in AI
- support to develop qualification frameworks for graduates in the field of AI.

Most enterprises indicate that one or another form of public support would help to strengthen staff skills in AI. Some 84% of enterprises indicate that partnerships with educational and vocational institutions would be either “very useful” or “moderately useful” (Figure 3.23). A similar share states that they would value support in developing qualification frameworks for graduates in the field of AI. Finally, 67% of enterprises indicate that tax allowances or tax credits for training in AI would be “very useful” or “moderately useful” (recall that most of the surveyed enterprises invest in R&D as part of the process of adopting and using AI).

## Figure 3.23. Perceived usefulness of support to strengthen staff skills in AI across 840 enterprises in G7 countries, 2022-23

Percentage of enterprises expressing agreement

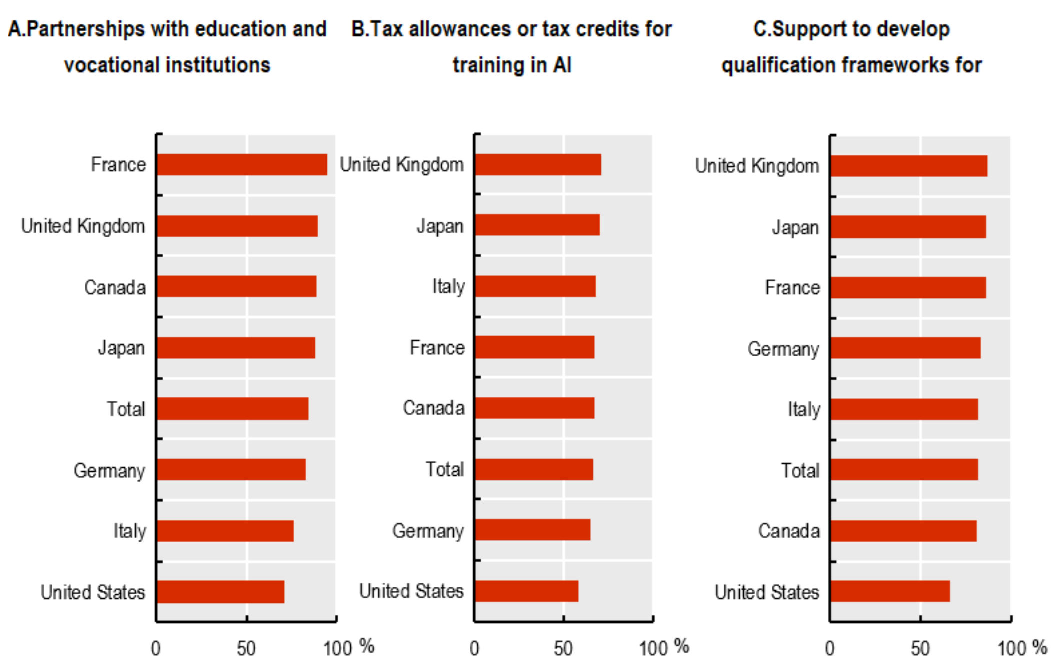



Note: The industry-size symbols present the sum of "very useful" and "moderately useful".
Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

As Figure 3.24 shows, large and small enterprises vary little in their assessment of the utility of support on human capital. Regardless of size, most enterprises consider that all three of the proposed ways of supporting the strengthening of workforce skills in AI are useful. The United States stands out as the country with the lowest share of enterprises that consider the surveyed means of support either moderately or very useful (Figure 3.24).

## Figure 3.24. Perceived usefulness of support measures to strengthen staff skills in AI across 840 enterprises, by G7 country, 2022-23

Percentage of enterprises that consider each type of support either moderately or very useful




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Across the survey sample just over 50% of enterprises use AI itself to facilitate training or to give cognitive support for workers. Such applications frequently combine AI with other technologies, such as augmented (AR) and virtual reality (VR). For example, using AR, workers might view useful information – such as how best to repair breakdowns in complex machine environments – on wearable visors. Among other applications, VR can enable safe and inexpensive "learning by doing", which is especially useful for beginners in tasks that entail safety risks or using expensive machinery. Using AI to provide training and cognitive support is one of the more recent applications of AI, which underscores the advanced-adopter character of some enterprises in the sample.

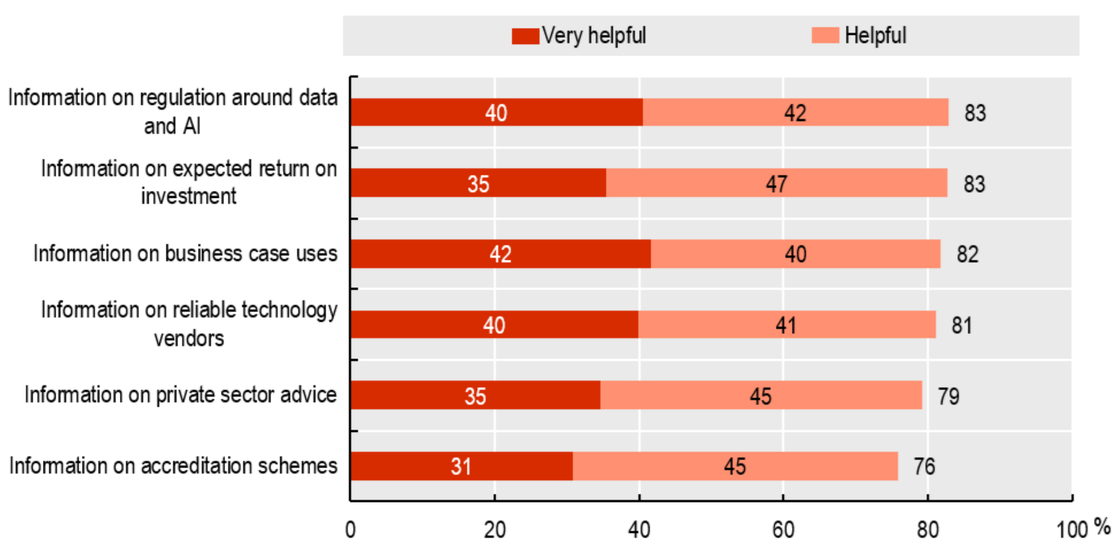
### *Public sector information services to assist in the adoption of AI*

Enterprises were queried on how helpful the following types of mostly information services provided by the public sector could be to their use and development of AI:

- information on and examples of business use cases in the firm's industry
- information on expected rates of ROI in AI
- information on available and reliable technology vendors
- information on available and reliable sources of private-sector advice and expertise
- certification or accreditation schemes for AI solution providers
- information on current or forthcoming regulations around data or AI.

A large majority of enterprises judge that information services provided by the public sector would be "helpful" or even "very helpful" to their use of AI. For any of the services considered, no less than 76% of enterprises indicate that they would be at least "helpful" (Figure 3.25). Fully 83% of enterprises judged that having more information on current or forthcoming regulations around data or AI or on expected ROI in AI would be either "helpful" or "very helpful".

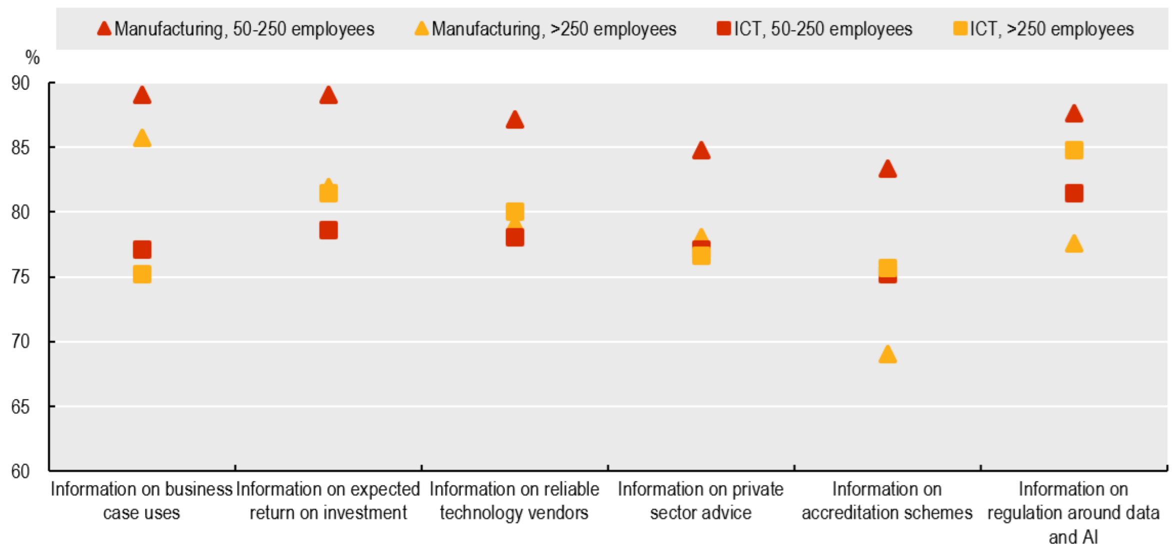
**Figure 3.25. Perceived usefulness of different services provided by the public sector across 840 enterprises in G7 countries, 2022-23**




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

It is notable that even in this sample of enterprises that often use AI in advanced ways, additional information on various domains of AI is sought. This suggests that such information may be even more important for firms that do not already use AI. Concerning differences across sectors and size of enterprise, Figure 3.26 shows that smaller manufacturers most often indicate that information services would be "helpful" or "very helpful". Differences due to enterprise size are much less pronounced among enterprises in ICT.

### Figure 3.26. Perceived usefulness across 840 enterprises in G7 countries of different services provided by the public sector, by industry and enterprise size, 2022-23




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises.*

Except for the United States, the share of enterprises indicating that information services are "helpful" or "very helpful" varies little across countries. In the sample, enterprises in the United States are least likely to consider public services as "helpful" or "very helpful".

### *Other public sector initiatives to support the uptake of AI*

The views of enterprises were also surveyed on the value of a wider set of public initiatives to foster the use of AI beyond information services. The initiatives considered were:

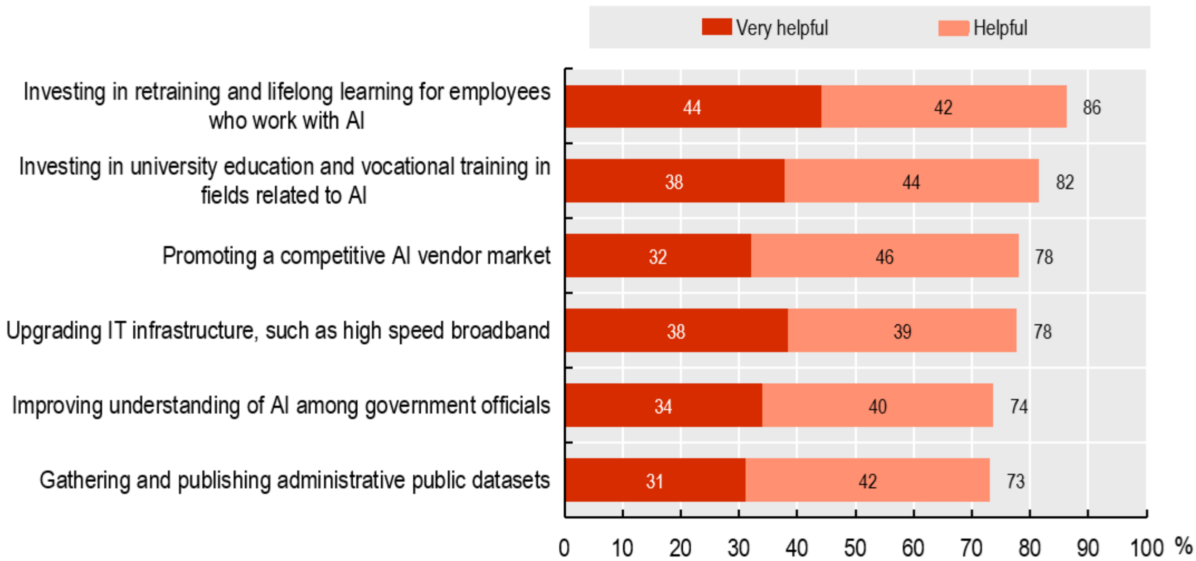
- investing in university education and vocational training in fields related to AI
- investing in retraining and lifelong learning for employees who work with AI
- improving understanding of AI among government officials
- gathering and publishing administrative public datasets
- promoting a competitive AI vendor market
- upgrading IT infrastructure, such as high-speed broadband

By taking into account the views of enterprises on the utility of identified areas of support, policy makers and organisations might more effectively promote the successful integration of AI technologies.

Most enterprises in the sample perceive all the listed public sector initiatives as "helpful" or even "very helpful" (Figure 3.27).

### Figure 3.27. Perceived usefulness of other public sector initiatives for AI adoption across 840 enterprises in G7 countries, 2022-23

Percentage of all enterprises




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

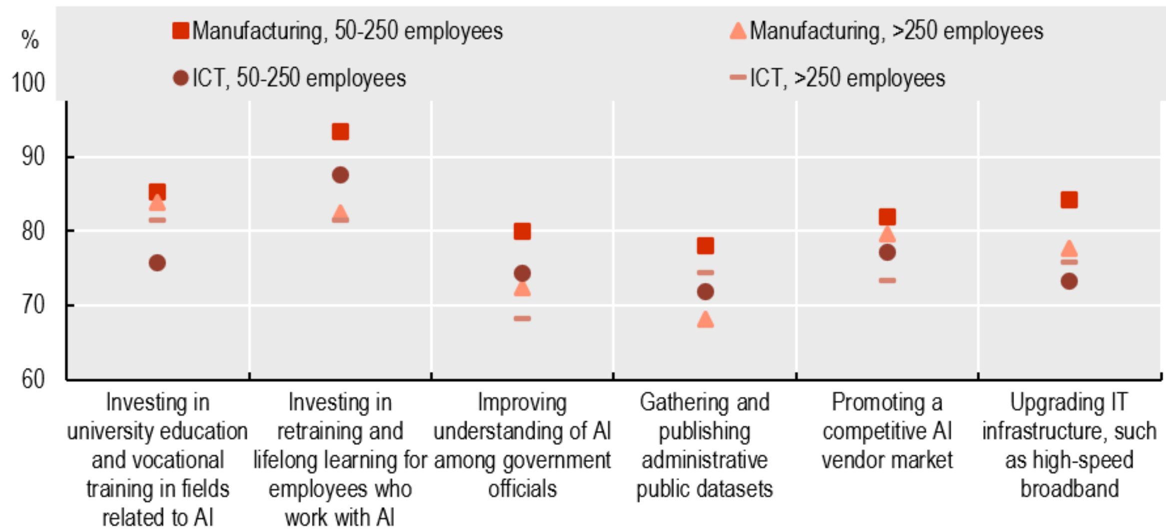
Among the most widely and highly valued initiatives are those to develop human capital. Some 86% of enterprises consider that initiatives that foster investments in retraining and lifelong learning for employees who work with AI would be “helpful” or “very helpful”. Similarly, 82% of enterprises consider public investments in university education and vocational training in fields related to AI to be “helpful” or “very helpful”. Such initiatives would not only provide students with specialised skills, but they could also contribute to the overall development of a workforce capable of driving innovation in AI. In addition, but slightly less prominent, the surveyed enterprises recognise the importance of enhancing government officials' understanding of AI, with 74% of enterprises rating this either “helpful” or “very helpful”.

Some 78% of enterprises believe that any measures to foster a competitive marketplace for AI vendors would be “helpful” or “very helpful”. By promoting a diverse range of vendors, enterprises might benefit from increased access to cutting-edge AI solutions and services. A reliable IT infrastructure is important for ensuring seamless connectivity and efficient data transfer, thereby facilitating the successful integration and deployment of AI technologies. Public initiatives aiming to upgrade IT infrastructure, such as high-speed broadband, are also supported by 78% of firms. Finally, 73% of enterprises perceive public sector initiatives that aim to gather and publish administrative datasets as “helpful” or “very helpful” for their adoption of AI. This finding emphasises the potential benefits of making administrative public datasets accessible to firms. Such datasets might serve as a resource for training and developing AI algorithms and models.

As depicted in Figure 3.28, the generally positive view towards this sample of possible public sector initiatives varies little in terms of industry and firm size. Even so, there are some subtle differences: smaller manufacturers tend to perceive the surveyed initiatives as “helpful” or “very helpful” most frequently.

## Figure 3.28. Perceived usefulness of other public sector initiatives for AI adoption across 840 enterprises in G7 countries, by industry and size, 2022-23

Percentage of all enterprises indicating "helpful" or "very helpful"

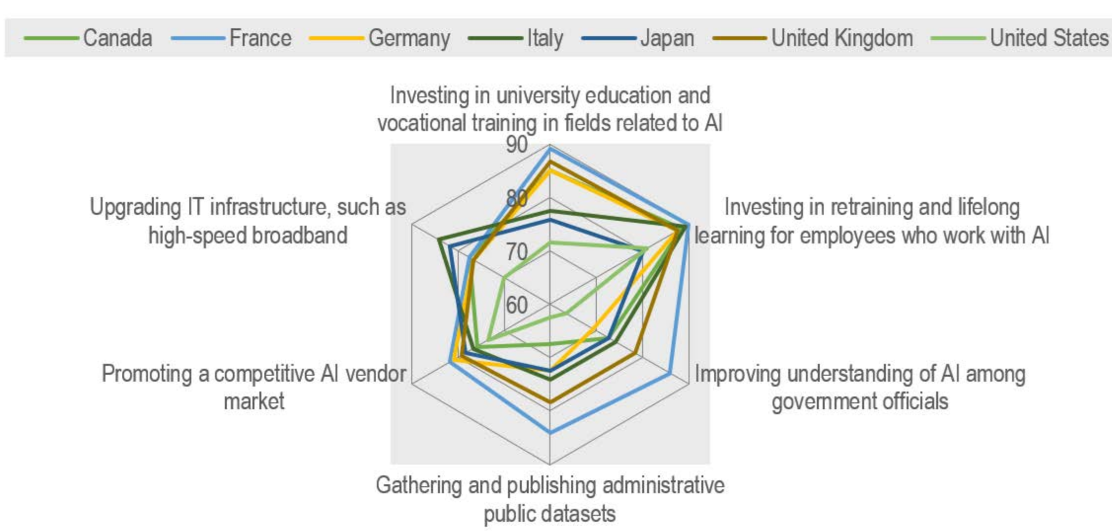



Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

With respect to country of location, somewhat larger differences in enterprises' perceptions can be detected (Figure 3.29). First, enterprises in the United States are least likely to report that public initiatives are "helpful" or "very helpful". Nevertheless, even within the United States, most enterprises hold a positive view of the types of initiatives considered in the survey. For instance, roughly 63% of enterprises in the United States state that initiatives to gather and publish administrative datasets are "helpful" or "very helpful". Overall, France exhibits the highest share of enterprises with a positive outlook on five out of six of the examined public sector initiatives.

## Figure 3.29. Perceived usefulness of other public sector initiatives for AI adoption across 840 enterprises, by G7 country, 2022-23

Percentage of all enterprises indicating "helpful" or "very helpful"




Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

### *Relating the adoption of AI to the use of public sector support*

This section examines the relationship between the use of public support and reported difficulties in adopting AI and cloud services, controlling for AI adoption rates.

First, enterprises that use more AI applications are more likely to use all three categories of public support. Large enterprises are less likely to use public support (Table 3.8). For instance, the estimated probability that a medium-sized enterprise will use public information and advice is 0.748, while the probability that a large enterprise will use the same public service is 0.684 (the probabilities come from a post-estimation that is not included in the table). For training services, the predicted probability is 0.640 for medium-sized and 0.508 for large enterprises. For access to finance, the predicted probabilities are 0.469 and 0.361, respectively, for medium-sized and large enterprises. These findings with respect to enterprise size are unsurprising since larger enterprises generally have more resources than medium-sized enterprises with which to resolve the challenges of AI adoption themselves. In addition, small and medium-sized firms are typically the main intended targets of public support for AI adoption. A further message here is that the probability of using these services is quite high overall and, as shown in Table 3.8, increases with the number of AI applications used.

Table 3.8 also shows that enterprises that report more obstacles to using cloud computing and more obstacles to using AI are more likely to use public sources of information and advice but not training services or access to finance and subsidies. A possible interpretation of these results is that lack of information is the biggest obstacle to overcome when adopting AI applications, while support for training and finance is only relevant once an AI application is adopted.

The parameters on the country and industry dummies were not statistically significant in the regressions, suggesting that the patterns of use of public support are similar across the G7 countries as well as across industries.

**Table 3.8. Enterprise characteristics and the probability of using three main forms of public support across 840 enterprises in G7 countries, 2022-23**

| Characteristic | Predicted average probability | | |
|---|---|---|---|
| | Information and advice | Training services | Access to finance |
| Number of AI applications | 0.117*** | 0.122*** | 0.153*** |
| | (0.024) | (0.022) | (0.022) |
| Number of reported limitations to using cloud computing | 0.112*** | 0.048 | 0.022 |
| | (0.040) | (0.038) | (0.038) |
| Number of obstacles to AI use | 0.107*** | -0.008 | 0.014 |
| | (0.037) | (0.035) | (0.036) |
| Enterprise size | -0.208** | -0.359*** | -0.308*** |
| | (-0.100) | (-0.092) | (-0.094) |
| Number of observations | 830 | 830 | 830 |
| Country fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Pseudo $R^2$ | 0.090 | 0.061 | 0.094 |

Note: Probit regressions use robust standard errors, country, and industry fixed effects. Robust standard errors are in parentheses. The three asterisks (***) and two asterisks (**) signify statistical significance at the 1% and 5% levels, respectively. Pseudo $R^2$ signifies the overall explanatory power of the regression, which may take values between zero and unity. The low levels of explanatory power here are typical of probit analysis.
Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

Earlier, it was seen that the questionnaire asked respondents to rate the helpfulness of the following five specific public sector services and initiatives:

- investing in education in fields related to AI
- investing in retraining for employees who work with AI
- improving understanding of AI among government officials
- gathering and publishing administrative public databases
- promoting a competitive AI vendor market

The respondents assigned scores ranging from “very helpful” (score 1) to “not helpful at all” (score 4). These responses were regressed on the number of AI uses and the number of obstacles to using AI reported by the enterprise, controlling for enterprise size, age, and industry (Annex H, Tables 1 and 2 report the regression results). The average score for public sector services and public sector initiatives is around 2, representing “helpful”.

Notably, the scores do not differ significantly with enterprise size or age. The only exception is the public initiative entitled “Investing in retraining for employees who work with AI”, which medium-sized enterprises value more than large enterprises. Furthermore, for this initiative, AI intensity does not affect the enterprises’ evaluation.

Of specific interest here is to what extent enterprises that use AI intensively or face many obstacles to using AI find public services and initiatives more helpful than those that use AI less intensively. The regressions suggest that they do. For instance, one additional AI application at the enterprise level is associated with a score of about 0.1 higher on the usefulness of “Public information on and examples of business use cases” in its industry. The service where experience with AI plays the least important role in terms of usefulness is “Information on available and reliable technology vendors”.

These use patterns, of course, cannot shed light on the actual efficacy of public support; the assessment of these would require other analytic approaches.

### *Support to facilitate the management of regulatory change*

The survey also elicited enterprises’ views on AI-related regulation. Some uses of AI that involve autonomous systems might be detrimental to clients, potentially exposing businesses to legal jeopardy. Enterprises were asked if they favour regulation that helps to overcome such a problem by establishing clear accountability when AI is used. A clear message is that enterprises seek clarity regarding accountability around the safe use of AI (Table 3.9). While the desire for clear accountability is unsurprising, these data underscore the need for policy makers to examine possible ambiguities that regulations might give rise to and how best to communicate information on regulation to firms.

### Table 3.9. Percentage of 840 enterprises in G7 countries favouring regulation establishing clear accountability when AI is used, 2022-23

Percentage of enterprises favouring clear regulatory accountability and the perceived usefulness of public services to this end

| | Enterprise would favour regulation establishing clear accountability when AI is used | |
|---|---|---|
| **Enterprise is aware that regulators are considering certification of the safety of AI systems** | Yes(n=736) | No(n=104) |
| Yes (n=666) | **92%** | 8% |
| No (n=174) | **71%** | 29% |

| | Usefulness of public services providing information on current or forthcoming regulations around data or AI | |
|---|---|---|
| | Very helpful or helpful (n=637) | A little helpful or not helpful at all (n=203) |
| | **81%** | 19% |
| | **56%** | 44% |

Source: OECD (2022-23[1]). *2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

## Conclusion

The OECD/BCG/INSEAD survey focuses on enterprises that utilise AI and compares AI use across G7 countries in two economic sectors (manufacturing and ICT) and two enterprise size classes. The sample size of 840 enterprises, while not statistically representative of national populations, allows for rigorous within-sample analysis. This within-sample analysis focuses on the intensive margin of AI use, exploring the number of AI applications adopted and their relationship to enterprise and industry characteristics.

The survey uses novel questions of direct policy relevance, addressing issues like the usefulness of public policies and support for AI adoption. Because the sample comprises many advanced AI users, the findings will likely become increasingly relevant to policy over time as more enterprises aim to become advanced AI users. However, as stated in Chapter 1, the survey was conducted prior to recent developments in generative AI and its rapidly expanding public use. It remains to be seen how the advent of generative AI affects patterns of AI adoption in firms.

A novel insight from the survey is the widespread positive view of public sector services to facilitate adoption, especially among enterprises facing obstacles to adoption or using AI intensively. Similarly, while initiatives to help develop human capital are highly valued, a non-trivial share of enterprises express uncertainty with respect to the precise skills they need, which suggests the value of developing new qualification frameworks. In addition, to aid in the use and development of AI, collaboration with universities and public research organisations is widespread, which underscores the importance of measures that facilitate these interactions, the need for which is also evident from interviews with enterprises (see Chapter 5).

As with any cross-sectional study, various results merit further examination using other methods. For instance, it would be helpful to better understand causal relationships associated with public sector support. For example, is the tendency for enterprises that use AI more widely to also use public support services driven by their encountering more diverse adoption challenges? Or might it be because more alert enterprise leadership will adopt AI more actively and more actively seek external assistance? Answers to questions such as these could inform decisions around the best allocation of public resources to support AI uptake.

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## Notes

[1] In future work, an alternative question might be tested, such as "Has your enterprise implemented a system of data governance?" Data management solutions can be local to individual divisions or activities within a business. Data governance, however, is essentially corporate-wide, and might therefore serve as a good proxy for data maturity overall. Thanks are expressed to Benoit Bergeret for this observation.

# 4 The goals and practices of institutions supporting the diffusion of artificial intelligence in firms

This chapter identifies the main mechanisms used by 19 institutions in the Group of Seven (G7) countries, plus Singapore, to help firms adopt AI. It finds that technology extension services can help firms define the business problem to be solved and develop proofs-of-concept that demonstrate how AI can help. In addition, grants for business research and development and applied public research remove part of the risk associated with AI investments. Business advisory services also provide non-technical assistance that can raise managers' understanding of their firms' AI readiness and the specific opportunities and challenges that AI entails. Furthermore, networking, and collaborative platforms help build AI ecosystems of public and private actors. In addition, on-the-job training can help address bottlenecks around AI skills. Finally, information services and open-source code provide helpful resources for firms seeking to strengthen their AI capabilities. The chapter seeks to draw lessons for designing and implementing such services.

## Introduction

Several technical features of artificial intelligence (AI) and broader characteristics of the markets faced by AI adopters have made its application more challenging than other digital technologies. Consequently, the uptake of AI in manufacturing firms, especially in small and medium-sized enterprises (SMEs), has been relatively low to date (see Chapter 2). Institutions supporting the diffusion and adoption of AI can help to address this issue. Many governments have ambitious national strategies that seek to achieve higher rates of AI uptake than would occur without active support for diffusion.

The OECD/Boston Consulting Group/INSEAD survey conducted among 840 enterprises in the Group of Seven (G7) countries in 2022-23 examines how the policy environment supports (or can support) enterprises attempting to adopt and/or develop AI applications. This chapter affords complementary evidence on the types of public support being provided for AI uptake and the experiences of firms using such support. The literature on AI adoption has not yet explored the role of institutions in technology diffusion in depth.

Institutions for technology diffusion are public or quasi-public bodies that facilitate the spread and use of knowledge and methods that assist firms in adopting technologies (OECD, 2017[1]). Diffusion institutions have a unique perspective on the AI adoption challenge, as they interact daily with a wide range of firms and organisations seeking to develop and implement AI applications.

This chapter presents evidence gathered through desk research, structured interviews and written contributions from 19 institutions promoting AI adoption in firms in the G7 countries plus Singapore.

The interviewed institutions confirmed the role of the obstacles to AI adoption described in prior literature. However, they lay greater emphasis on some specific issues. They highlight uncertainties about the return on investment (ROI) as a significant barrier to firms adopting AI. Managers frequently struggle to grasp how AI can address real-world challenges in the workplace. They also tend to underestimate the implications of deploying AI solutions, which can require considerable changes in business culture and practices across many (if not all) segments of the firm. Many firms fail to apply AI due to limited access to AI skills and insufficient data maturity. Furthermore, regulatory uncertainties can deter enterprises from making efforts toward adoption.

This chapter identifies seven main mechanisms that diffusion institutions use to assist firms in overcoming the challenges of adopting AI:

1. Technology extension services can help firms narrow down and describe business problems to be solved and develop proofs-of-concept that demonstrate how AI can help.
2. Grants for business research and development (R&D) and applied public research mitigate some of the risks associated with AI expenditures.
3. Business advisory services provide non-technical support to managers, helping them improve their understanding of their firm's AI readiness, opportunities, and challenges.
4. Grants for applied public research which can help promote high-risk research and/or the development and implementation of technologies close to commercialisation.
5. Networking and collaborative platforms aid in developing public and private AI ecosystems, increasing demonstration effects, and facilitating knowledge transfer.
6. On-the-job training can assist firms in solving constraints around AI skills.
7. Information services and open-source code provide helpful resources for firms to raise their AI capabilities.

To optimise their service offering, diffusion institutions frequently blend these mechanisms.

## The role of diffusion institutions in promoting AI adoption

### *Rationales for the existence of diffusion institutions*

AI's economic and societal benefits will only materialise if the technology is responsibly designed, widely diffused, and adopted. Besides the firm-level barriers to the adoption of AI referred to in Chapter 2, certain market and systemic conditions may also lead to socially suboptimal adoption. Research and technology policies have generally emphasised support for basic science and R&D more than technology diffusion and adoption. There are several reasons why a greater focus on technology diffusion could be socially beneficial.

Governments may have strategic economic goals that require rates of AI uptake to be faster than would occur without active support for diffusion. For example, labour productivity has stagnated in OECD countries for decades. Technological upgrading in firms is essential to offset this stagnation. Increasing the average value of output per hour worked is more urgent still in the current context in which OECD populations are ageing rapidly and, as a consequence, the share of the population in work is falling while public spending on health and social care is rising rapidly. Even if there is a direct outlay of public resources to facilitate the uptake of AI and other productivity-enhancing technologies, the wider economic benefits of increased productivity may exceed the associated costs.[1] Achieving a more balanced pattern of economic activity at the subnational level (e.g. regions) is another case where an overarching economic and social policy priority could justify spending on institutions to accelerate the uptake of AI and other productivity-enhancing technologies.

As described in Chapter 2, relatively few firms, particularly SMEs, have adopted AI. Consequently, the wider business community may see relatively few examples of successful use cases. In this context, diffusion institutions can help increase spillovers of useful information. They can provide information on examples of successful uses of AI while documenting implementation methods, business models, risks and other details that other companies might replicate. Useful information need not be limited to successful applications of AI: even if a firm's attempt to adopt AI fails or an AI start-up collapses, valuable information is still created for others to learn from (e.g. pitfalls that should be avoided). However, entrepreneurs and businesses that generate this socially beneficial information receive no reward for doing so. Institutions that facilitate the diffusion of AI can aid the spread of economic and technological information about all aspects of AI in business.

Another problem that can arise in markets for relatively new technologies such as AI is the lack of specialised services supply. In the early stages of a technology's market penetration, providers of complementary business and advisory services and specialised software often target large firms. This may happen due to the greater complexity and cost of working with large numbers of SMEs and because larger firms are better able than SMEs to bear the associated risks and costs. To address this, one step that diffusion institutions can take is to help SMEs understand the services and information provided by AI suppliers and help lower search costs for SMEs trying to identify services of reliable quality and relevance to their specific needs.

Finally, although less directly relevant to AI adoption in firms, diffusion institutions can also generate knowledge that informs policy making. Since these institutions work directly with firms, they have primary information about the needs, obstacles, and opportunities facing the private sector, as well as what policy settings best work for AI adoption. This information can be channelled into the policy-making process to improve the pertinence and quality of policies to support AI adoption.

### *Mechanisms used by diffusion institutions*

Between April and August 2022, the OECD undertook 18 structured interviews with institutions in G7 countries that work to accelerate the diffusion of digital and other technologies in the business sector, including AI (for the sake of clarity and brevity, these institutions are hereafter referred to as “AI diffusion institutions”). The interviews explored how these institutions promote AI adoption. Public bodies and publicly funded non-profit organisations were identified through the OECD AI Observatory,[2] the Science, Technology and Innovation Policy Compass[3] database, and conversations with industry experts and delegates to the OECD’s Committee for Scientific and Technological Policy. AI Singapore was also invited to participate, as this institution has employed a number of novel approaches to diffusion, from which lessons might be drawn that are helpful to other countries.

The interviews first aimed to characterise each diffusion institution and how it supports AI adoption, complementing information already available online. They then explored each institution’s experiences and understanding of the main barriers to AI adoption in firms and other organisations, including awareness of what AI can do, staff skills and difficulties estimating the ROI. Finally, interviewees were asked to describe the institutions’ views on the most effective forms of support to overcome barriers to AI adoption. Annex I includes the core list of questions used to structure the interview. The questions were adjusted to the specificities of each institution using the information found online. Table 4.1 lists the participating institutions and sets out the mechanisms they use to promote AI adoption.

## Table 4.1. Institutions interviewed for this study and the diffusion mechanisms they use

| Country | Institution | Technology extension services | Grants for business R&D | Business advisory services | Grants for applied public research | Networking and collaborative platforms | On-the-job training | Information services and open-source code |
|---|---|---|---|---|---|---|---|---|
| Canada | Vector Institute | X | | | | X | | |
| Canada | Scale AI | X | X | | | X | | |
| Canada | National Research Council-Waterloo Collaboration on AI, IoT and Cybersecurity | X | X | | X | X | X | |
| Canada | Forum IA Québec | X | | | | | | |
| France | Ministry of Ecology, “AI and Green Transition” programme | | | | | | X | |
| France | Cap Digital | X | X | | X | | | |
| Germany | Fraunhofer Institute for Industrial Engineering IAO | X | | X | | | | X |
| Germany | German Research Centre for Artificial Intelligence (DFKI) | | X | | | X | X | |
| Germany | Plattform Lernende Systeme | | | | X | X | | |
| Germany | Mobility Data Space | | | | | | | X |
| Italy | Artificial Intelligence Research and Innovation Centre (AIR) | | X | | | | | |
| Italy | Siena Artificial Intelligence Hub (SAIHub) | | | | | | | |
| Japan | New Energy and Industrial Technology Development Organization (NEDO) | X | X | | | X | | |

| Country | Institution | Technology extension services | Grants for business R&D | Business advisory services | Grants for applied public research | Networking and collaborative platforms | On-the-job training | Information services and open-source code |
|---|---|---|---|---|---|---|---|---|
| United Kingdom | National Health Service (NHS) AI Lab | | | X | | | | |
| United Kingdom | Digital Catapult | | | | X | | | |
| United Kingdom | techUK | | | X | | | | |
| United States | Manufacturing Extension Partnership (MEP) | X | | | | | | |
| United States | Digital Manufacturing and Cybersecurity Institute (MxD) | X | | | | X | | |
| Singapore | AI Singapore (AISG) | | X | X | X | X | X | X |

Each of the following sections focuses on a given mechanism used by diffusion institutions, i.e. technology extension services, grants for business R&D, business advisory services, funding for applied research, networking and collaborative platforms, on-the-job training, and information services and open-source mechanisms (Box 4.1). These sections also introduce the interviewed diffusion institutions, describing how they use the various mechanisms.

### Box 4.1. Mechanisms used by technology diffusion institutions to promote AI adoption

- **Technology extension services**: Technology assistance provided by technology or research organisations with expertise in AI research and its applications. Rather than aiming for new technological breakthroughs, these services adapt established AI solutions for firms and other organisations. The services can be funded through public support, contractual services paid by firms, or a mix of public and private sources.
- **Grants for business R&D**: A direct allocation of funding for companies to invest in R&D to develop an AI application. Grants can be allocated to individual firms of different sizes (e.g. start-ups, SMEs, large firms) or a consortium involving research organisations. Beneficiaries often make a matching contribution and co-finance their R&D projects.
- **Business advisory services**: Assistance that promotes innovation and entrepreneurship by supporting business processes. These can include readiness assessment, market studies, fundraising and business design coaching, and support for business R&D grant applications, among other types of assistance. While these services do not foster technology transfer or the implementation of AI solutions per se, they can provide valuable guidance for businesses wishing to adopt AI.
- **Grants for applied public research**: A direct allocation to universities or other public research organisations seeking to finance AI research projects. Such projects conduct experimental work to enlarge the technological frontier. They involve industry actors that sometimes co-finance research expenditures and provide other in-kind resources (e.g. staff time, data used to train AI). Depending on the project, the pathway to research commercialisation can vary in duration, from months to more than ten years.
- **Networking and collaborative platforms**: Associations that gather a set of actors within the AI research and innovation system, often sharing common geographical locations. These platforms include industry players such as entrepreneurs, investors and companies, as well as public sector entities such as universities, research institutes and funding agencies. They can

help a range of actors monitor the state-of-the-art in commercial AI technologies and their applications, match buyers and sellers of AI solutions, and support the fundraising efforts of AI start-ups, among other types of support.

- **On-the-job training**: Courses or instruction offered to employees and provided in parallel to their work, with the aim of deepening AI-related knowledge and skills. Different courses are offered to technical employees (e.g. data engineering, machine learning [ML]) and business executives (e.g. developing AI business plans and strategies). While not a substitute for tertiary education, on-the-job training helps employees contextualise coursework with the specific challenges and requirements of work.
- **Information services and open-source code**: Infrastructures and related resources that develop and maintain datasets or software that firms can use to develop AI applications. Firms, industry experts and other stakeholders participate in building the infrastructures and resources to ensure their relevance and applicability in business use cases.

Source: Adapted from EC/OECD (EC/OECD, 2023[2]), *EC/OECD Science, Technology and Innovation Policy (STIP) Survey*, https://stip.oecd.org/assets/downloads/STIPCompassTaxonomies.pdf; OECD (2017[1]), "The next production revolution and institutions for technology diffusion", https://doi.org/10.1787/9789264271036-11-en; interviews with AI diffusion institutions.

### *Technology extension services*

Technology extension services are commonly offered by research technology organisations (RTOs). These organisations are primarily concerned with developing and transferring research and technology to the private sector and society at large (Sanz-Menéndez et al., 2011[3]). Unlike other research organisations, which are chiefly driven by scientific research, RTOs are often established to provide scientific and technological solutions to the wider economy in their specific fields of competence. They are generally publicly funded (through block funding and competitive research grants) as well as industry-commissioned projects.[4]

An example of an RTO of this sort is Germany's Fraunhofer Institute for Industrial Engineering IAO,[5] which works with large companies and SMEs to realise the promise of AI and other emerging technologies, including blockchain, autonomous vehicles and Internet of Things (IoT) platforms. This Fraunhofer Institute transfers AI research through contractual services supporting product engineering, process development, and systems development and implementation. Over the past two years, the Institute has run around 200 projects.[6] Many of these are carried out in collaboration with the Fraunhofer Institute for Manufacturing Engineering and Automation IPA[7] in their jointly managed AI Innovation Centre.[8] The AI Innovation Centre receives funding from the Ministry of Economic Affairs, Labour and Tourism of Baden-Württemberg and provides expert advice on getting started in AI and robotics[9] free of charge for companies.

Based in Toronto, the Vector Institute[10] is an autonomous not-for-profit corporation committed to AI research, specialising in ML and deep learning. It was established in 2017 with financial support from the Government of Canada, the Government of Ontario, and private sector actors in partnership with the University of Toronto. Its mission is to work with firms, research organisations, start-ups, incubators and accelerators to advance AI research and steer its application, adoption and commercialisation across Canada. The Vector Institute offers technology extension services delivered through industry sponsorships. Based on the success of the Vector Institute's industry programmes, it is now adapting them to help SMEs through its FastLane Program,[11] which gives SMEs access to talent, training and networking opportunities. The FastLane Program is federally funded and does not require payment from SMEs to join.

The Hollings Manufacturing Extension Partnership (MEP) provides technology extension services to SMEs based in the United States. These services include technology scouting and transfer, supplier scouting, business-to-business network pilots, technology-driven market intelligence and co-operative R&D

(Sargent, 2019[4]). The MEP programme is housed at the US Department of Commerce's National Institute of Standards and Technology (NIST). The programme has MEP centres in all US states and Puerto Rico and more than 1 450 trusted advisors and experts at approximately 430 MEP service locations.

Non-profit institutions, higher education institutions, US states and territories, and local and tribal governments can compete to establish an MEP Centre. The federal government may provide up to 50% of the funding necessary to create and operate a given centre. To be eligible, the MEP Centre must secure at least half of the financing through non-federal sources, such as state governments or service fees. After an SME submits a manufacturing problem statement to its local MEP Centre, staff there undertake assessments involving factory visits. In this process, they evaluate business use cases and may identify opportunities where AI could help. In implementing projects, MEP works with firms to develop AI solutions using its in-house experts or subcontractors, including research organisations and industry actors.

MEP clients, or any US manufacturer, can also apply to the MEP-Assisted Technology and Technical Resource (MATTR) service[12] to work with NIST research laboratories and user facilities. This service gives companies access to further technical expertise and engineering capabilities in advanced manufacturing, collaborative robotics, cybersecurity, and information and communication technologies, among other fields, often at no cost.

The Italian Artificial Intelligence Research and Innovation Centre (AIRI)[13] is an interdepartmental centre explicitly created to conduct industrial research and AI technology transfer. Its staff comprises professors, researchers and postgraduate students from the University of Modena and Reggio Emilia's departments of Engineering, Economics, and Physics, Informatics and Mathematics. AIRI conducts basic and applied research. The latter can be considered a form of technology extension service, as it exclusively involves companies with high technology readiness and close-to-market projects that could have significant business impact.[14] The Emilia-Romagna region provides subsidies equivalent to about 30% of project costs; the remainder is funded by beneficiary companies.

The United Kingdom's National Health Service (NHS) created the NHS AI Lab[15] in 2019 to help deliver the promises of AI in the health sector. The NHS AI Lab gathers government, health and care providers, academics, and technology companies to create opportunities for collaboration and technology co-creation with a view to addressing challenges in developing and implementing AI systems. It also aims to develop the use of synthetic data for AI applications in healthcare. It uses various diffusion mechanisms, including a technology extension service called "AI Skunkworks". In the AI Skunkworks programme, NHS AI Lab experts and external solution providers work with healthcare providers (e.g. hospitals and health centres) on data-rich problems in care delivery to develop proofs-of-concept and demonstrate if and how AI can tackle them.

### *Grants for business R&D*

Set up by United Kingdom Research and Innovation (UKRI) in 2013 and part of the Catapult Network, the Digital Catapult[16] is a partly publicly funded research technology organisation that encourages early adoption of innovative digital technologies. It supports projects that might subsequently be replicated by UK businesses more broadly. Digital Catapult focuses on accelerating the adoption of virtual and augmented reality, 5G and IoT, blockchain and AI technology as individual technologies – and also in combination in emerging complex systems, such as the Metaverse and digital twins.[17] One example of a supply-side programme delivered by Digital Catapult that supports AI start-ups is the Made Smarter Technology Accelerator (MSTA).[18] MSTA is a matching-fund programme that invites medium and large manufacturing companies to define and scope business challenges that advanced digital technologies such as AI can solve. Digital Catapult then solicits solutions to these challenges from the United Kingdom's technology and digital start-up ecosystem – validating their suitability and supporting the process of collaboration.

Based in Canada, Scale AI[19] is a consortium of enterprises, research centres, academic bodies and high-potential start-ups dedicated to the diffusion of AI technologies. In its mission statement, it pledges to support: 1) investments in developing AI applications across supply chains; 2) the commercialisation of AI-powered solutions; 3) the AI start-up ecosystem; 4) AI skills in the workforce; and 5) the collaborative development of AI applications. It is one of Canada's Global Innovation Clusters, supported by Innovation, Science and Economic Development (ISED) Canada.[20] Scale AI provides grants for industry-led projects[21] in demand forecasting, automated in-plant logistics and real-time data integration. Government funding is matched by contributions from the private sector, with Scale AI reimbursing up to 50% of expenses for approved projects (of which there are about 30 per year).

Based in the United States, the Digital Manufacturing and Cybersecurity Institute (MxD)[22] aims to transform US factories by fully equipping them with the digital tools and expertise they need to reduce costs, grow and improve their operations, and become globally competitive. It is part of Manufacturing USA,[23] a network of regional institutes with diverse technological focuses. MxD has invested over USD 120 million (US dollars) (about EUR 120 million [euros]) in more than 85 applied R&D projects[24] in the areas of design, product development, systems engineering, future factories, agile and resilient supply chains, and cybersecurity. The development and implementation of AI solutions are often embedded in many of these projects.[25] MxD awards up to USD 75 000 (about EUR 75 000) to teams composed of at least one post-secondary academic institution. MxD prioritises groups that include at least one industrial partner, which has to provide matched funding and/or in-kind contributions.

Japan's New Energy and Industrial Technology Development Organization (NEDO)[26] is a public agency supporting R&D that addresses energy and global environmental problems and develops new advanced technologies. It does not conduct its own research but formulates technology strategies and programmes and, as part of its R&D project management activities, establishes implementation frameworks combining the capabilities of public-private actors in industry, academia, and government. NEDO supports basic and applied research on high-risk, innovative technologies. It has two main R&D programmes supporting AI diffusion in firms:

- Development of Integrated Core Technologies for Next-Generation AI and Robots: Spanning the years 2018-23, and with a 2022 budget of JPY 1.40 billion (Japanese yen) (about EUR 9.6 million), the programme assists R&D and technology demonstration in areas such as business analysis, data gathering and processing, AI model development and impact assessment. It also supports AI projects involving business inventory optimisation, decision making and improved efficiency.[27]
- Realisation of a Smart Society by Applying Artificial Intelligence Technologies: This programme, spanning the years 2018-22, and with a 2022 budget of JPY 1.375 billion (about EUR 9.4 million), funded AI R&D and technology demonstration using data-acquisition sensor technologies (IoT) in three strategic sectors: health, medical care and welfare, and mobility.[28]

The French Ministry of Ecology is launching an AI and Green Transition Programme.[29] This initiative seeks to support AI demonstrators in reducing carbon emissions and addressing other environmental challenges in public services and the public sector. Eligible projects must be led by regional governments, municipalities, and other parts of the public administration and must involve local companies or research organisations. Projects must have a budget of at least EUR 1 million for developing AI systems capable of making recommendations, forecasting or decision making. Examples of expected proposals include raising energy efficiency in buildings, visual image analysis to detect unauthorised waste disposal and optimising public transportation services. The programme will support between 50-70% of applied R&D expenses and 25-45% of experimental development expenses, depending on the size of the beneficiary firm.[30] Projects involving collaboration with one or more SMEs or research organisations receive more public funding.

Two diffusion institutions providing technology extension services also manage business R&D grants. Fraunhofer IAO organises and co-ordinates consortia for collaborative research projects – involving industrial and research partner organisations – funded by the German government and the European Union. For instance, its AI Innovation Seeds[31] programme gathers a group of 5-12 firms to explore new AI approaches to address challenges of common interest, with funding from the Ministry of Economic Affairs, Labour and Tourism of Baden-Württemberg. The NHS AI Lab runs an AI in Health and Care Award,[32] which has committed around GBP 90 million (about EUR 108 million) in over 70 awards for companies to accelerate the testing and evaluation of strategic AI technologies for healthcare. The award aims to speed up real-world applications by helping build an evidence base demonstrating their effectiveness and safety.

AI Singapore[33] is a national AI programme launched by Singapore's National Research Foundation and hosted by the National University of Singapore. One of the programme's primary missions is to support AI adoption in firms, and to this end, it manages a suite of diffusion mechanisms.[34] Its 100 Experiments (100E)[35] flagship initiative provides business R&D grants to solve firms' AI challenges and help them build their own AI teams. A company can apply by submitting a problem statement that cannot be readily tackled using third-party applications and that could be solved within 9 to 18 months by Singapore's ecosystem of AI researchers and engineers. AI Singapore provides selected projects with up to SGD 250 000 (Singapore dollars) (about EUR 179 000) for Singapore's universities and research institutes to work with companies. Beneficiaries provide matching funds and in-kind contributions (i.e. staffing in AI disciplines, engineering resources, etc.). AI Singapore assigns its staff to an engineering team that joins the project and develops an AI minimum viable model. Such staff typically includes full-time AI engineers, data scientists and apprentices from the AI Apprenticeship Programme (see below).

#### *Business advisory services*

Besides offering technical expertise, diffusion institutions can provide non-technical guidance to managers and executives to support AI adoption. Cap Digital,[36] for example, is a French association of companies specialising in digital technologies (including AI). It provides fundraising support and business coaching services to help its members learn how to pitch to different audiences and seize opportunities in foreign markets. Cap Digital also provides R&D support services to member firms interested in applying to regional, national and European calls for grant proposals and tenders. It helps companies prepare applications by providing expert assessments and supporting partner search (such as other companies and research institutions) to form grant consortia. Cap Digital is funded by a mix of public and private sources, including the French national government and regional councils of the Paris Region and Hauts-de-France, as well as through membership and professional services fees.[37]

Diffusion institutions can offer business advisory services in combination with other AI diffusion mechanisms. Fraunhofer IAO, for example, complements its technology extension services with business guidance. Business and public sector bodies can commission feasibility studies, market and trend studies, strategy development and organisational design. Diffusion institutions can also combine grants for business R&D with business advisory services to address weaknesses in business technology upgrading efforts and financial constraints (OECD, 2017[1]). For example, Digital Catapult's start-up acceleration programme "FutureScope" delivers an AI initiative called the Machine Intelligence Garage,[38] which provides access to computational resources to early-stage start-ups with high growth potential to help develop and test new products and services. Such resources include cloud credits for partners such as Amazon Web Services and Google Cloud, as well as specialised and independent hardware support and advice from partners such as Graphcore and Nvidia. The programme gives practical guidance to help AI start-ups build sustainable and ethical solutions. It also provides access to fundraising opportunities, as well as technical support from industry leaders who have partnered with the programme.

Scale AI also has an AI Acceleration[39] programme that supports Canada's SME and start-up ecosystem. It does not fund individual companies but instead gives financial support to organisations that fund firms, including incubators, accelerators, innovation centres, corporate labs and open innovation initiatives. Eligible organisations also provide support services such as coaching, mentorship, customer and business development assistance, intellectual property and commercialisation assistance, product expansion and fundraising support. These organisations can receive up to CAD 50 000 (Canadian dollars) (about EUR 37 000) from Scale AI for each supported start-up working to build applied AI products and services for supply chains. Applicable costs eligible for reimbursement include wages and salaries for activities and expenses related to equipment, labs, facilities, supplies and materials.[40]

AI Singapore has a framework that helps companies and other organisations assess their existing capabilities and opportunities to adopt AI. Further, it helps them identify obstacles that need to be overcome to achieve more advanced readiness (Table 4.2). Under this framework, AI Singapore provides business advisory services delivered through workshops and six-week AI solutions development projects.

## Table 4.2. AI Singapore's AI Readiness Index

| | AI-unaware (Less than 1) | AI-aware (1 to 1.9) | AI-ready (2 to 2.5) | AI-competent (More than 2.5) |
|---|---|---|---|---|
| General capabilities | Might hear about AI but is unaware of applications | Savvy consumers of AI solutions. Capable of identifying use cases for AI applications | Capable of integrating pre-trained AI models into products or business processes | Capable of developing customised AI solutions for specific business needs |
| General characteristics | Wait for vendors to convince use cases and business value of AI | Identified potential use cases and seeks AI solutions from vendors | Evaluated the viability of pre-trained AI models | Developed a roadmap for AI implementation |
| AI adoption suitability | Consume ready-made, end-to-end AI solutions | Integrate pre-trained AI models and solutions for common AI applications | Integrates pre-trained AI models and solutions for common AI applications | Develop customised AI model for unique business needs |

Note: Numbers under each category represent average score ranges.
Source: AI Singapore (2024[5]), *AI Readiness Index (AIRI)*, https://aisingapore.org/airi.

### *Grants for applied public research*

In addition to providing financial support to companies, diffusion institutions can fund AI research conducted in universities or public research institutes. This research is generally performed in collaboration with industry actors and can support high-risk research or the development and implementation of technologies close to commercialisation. Canada's National Research Council (NRC) - University of Waterloo Collaboration on AI, IoT and Cybersecurity[41] is an example of such a programme. The university works with companies in Ontario to develop promising AI technologies that do not have a clear path to commercialisation. The average commercialisation timeframe usually ranges between five to ten years, depending on the project.[42] The German Research Centre for Artificial Intelligence (DFKI),[43] funded by the Federal Ministry of Education and Research, conducts "human-centric" AI research in the search for technology and application breakthroughs. It hosts public-private research partnerships with software, automotive and manufacturing companies. A quarter of DFKI activities in a given year involve work with industry actors. Commercialisation of the research it supports is typically ten years away at least.[44]

Besides supporting applied AI R&D in businesses, NEDO also operates two programmes supporting applied research led by universities and public research institutes:

- Technology Development Project on Next-Generation Artificial Intelligence Evolving Together with Humans spans the period 2020-24 and, in 2022, had a budget of JPY 2.68 billion (about EUR 18 million). This programme supports the development of interactive AI systems that work together with humans. More specifically, the programme will support research that: 1) facilitates human understanding of AI decisions and decision-making processes; and 2) develops mechanisms for human inputs to improve the inference accuracy of AI.[45]

- Development of AI-Based Innovative Remote Technologies spans the period 2021-24, and in 2022, had a budget of JPY 500 million (about EUR 3.5 million). This programme funds R&D on AI for extended reality systems that comprehensively and accurately depict remote environments and transmit information visually, aurally and through haptics.[46]

AI Singapore manages two programmes supporting close-to-market public research:

- The AI Grand Challenge[47] initiative funds research in collaboration with the public sector that aims to solve national challenges. For example, the "AI in Health Grand Challenge" supported research to enhance primary healthcare and disease management in Singapore. The "AI in Education Grand Challenge," co-organised with the Ministry of Education, will follow a similar model to support mother-tongue language learning for primary-level students in Singapore.
- The AI Technology Challenge[48] aims to develop innovative AI solutions that can be adopted in government and business sectors that are strategically relevant to Singapore. Funded research projects are conducted in collaboration with a government office or an industry partner.

AI Singapore's Technology Offers[49] promotes science-industry collaborations to create new products or services to support the commercialisation of the research results obtained from these programmes. Its catalogue offers more than 15 AI solutions developed from past research for firms to adopt. These cover a range of business sectors, including healthcare, biochemistry, manufacturing and transportation.

### *Networking and collaborative platforms*

Diffusion institutions can bring together firms, higher education and research institutions, and other public and private entities to facilitate collaboration around AI diffusion. They provide networking services to match the supply and demand for AI technologies and applications and promote a collective pool of knowledge to increase participants' productivity, innovation and competitiveness.

Networking and collaborative platforms sometimes have a regional focus. Based in Italy, the Siena Artificial Intelligence Hub (SAIHub)[50] aims to gather AI SMEs, large companies and research actors in the Tuscany region. To attract talent, it creates partnerships with the University of Siena to propose scholarships and cash prizes[51] for students who, after completing the master's degree course or doctorate, begin their professional activity at one of the more than 30 companies of the SAIHub Network. The hub also promotes AI services and solutions offered by member SMEs.[52] Based in Montreal, Forum IA Québec[53] aims to support the region's AI ecosystem. To this end, it offers several informational and other resources to help firms adopt AI. For instance, its open directory[54] of AI actors includes information on consulting firms, solution providers, research and technology transfer institutions and venture capital funds. The directory also includes a collection of AI use cases and funding opportunities. Forum IA Québec also conducts assessments of the performance of the region's AI ecosystem to inform policy decisions.

Other platforms operate at a national level. Plattform Lernende Systeme,[55] for example, brings together AI specialists from science, industry, government and civic organisations to promote adoption and inform policy makers and other stakeholders. It was set up by the German Federal Ministry of Education and Research and managed by the German National Academy of Science and Engineering (acatech). The Plattform hosts a variety of working groups in areas such as the future of work, healthcare and mobility to examine the prospects, challenges and prerequisites for developing socially responsible AI. It has introduced a national Map on AI[56] that includes information on more than 1 100 use cases and hundreds of research institutions, knowledge intermediaries and study programmes. It also provides various forms of business intelligence, including market and technology analyses and thematic reports. Based in London, techUK[57] is a trade association that gathers individuals, businesses, government, and stakeholders to deliver the promises of digital technologies. It includes AI as one of its six technology focus areas and has about 500 member SMEs (technology providers). The association is active in: 1) analysing and formulating policy proposals for the adoption of digital technologies; 2) promoting the use of technologies in business sectors such as financial services, defence, manufacturing, utilities and consumer electronics; and 3) monitoring emerging trends in technologies and innovation (e.g. digital twins).

Some of the interviewed institutions use other diffusion mechanisms to foster opportunities for networking and establishing collaborations:

- The Vector Institute offers services that help companies identify and hire AI talent through its FastLane programme. It hosts the "Digital Talent Hub" online platform that links employers with skilled AI talent seeking employment. The Institute organises recruiting events, executive networking events and research symposia.
- The MEP's Supplier Scouting Service[58] helps manufacturing SMEs connect to suppliers with the right technical and production capabilities. The service operates on a national, regional and local level to connect suppliers with purchasers higher up the supply chain, including larger companies and government agencies.
- Enterprises, research centres, education institutes, start-ups and other actors in the Canadian AI ecosystem can join Scale AI as associates at no cost. This membership allows them to benefit from networking opportunities, including matchmaking and informational events.[59]
- Cap Digital, mentioned in the previous section, organises more than 100 events each year with more than 1 000 members to provide networking opportunities and promote their innovative technologies and services.
- AI Singapore's The Epoch[60] web portal aims to be a digital platform supporting the country's AI ecosystem of students, teachers, apprentices, professionals and SMEs. The site, open to all and free of charge, seeks to create networking opportunities, host exchanges around learning and applying AI in the workplace, and publish community-contributed articles and job opportunities.

### *On-the-job training*

While training services are not a mechanism central to the interviewed diffusion institutions, many recognise that firms often struggle to adopt AI due to the lack of skilled staff. This deficiency can limit what companies can gain through AI technology extension services or grants for business R&D. To tackle this obstacle to adoption, some institutions propose courses or training for professionals as a complementary diffusion mechanism:

- The Vector Institute offers training courses[61] to raise management and technical staff skills and improve awareness of AI applications. Some courses invite business leaders to analyse real-world AI use cases and identify opportunities and challenges underpinning successful adoption. The Vector Institute likewise hosts applied and research internships[62] that allow participants to work alongside AI engineers and researchers.
- As part of its statutory activities, the MEP facilitates training (offering courses in-house), supports new or existing apprenticeships, and provides access to information and experts that can help address workforce needs and skills gaps (Sargent, 2019[4]). Examples of AI training courses targeting SMEs include those offered by North Carolina MEP and South Carolina MEP.[63]
- Scale AI provides training support for working professionals by covering half their registration fees for more than 180 accredited courses proposed by partner training programmes.[64] It also offers grants for companies to develop tailored on-the-job training courses[65] for their employees, covering up to 85% of CAD 100 000 (about EUR 74 000) in eligible expenses.
- MxD's Virtual Training Centre[66] is an online platform that assists manufacturers and workers in skills development. It gives access to more than 1 000 free and paid courses on cutting-edge

technologies (including 48 centred on AI) offered by Google, Microsoft, Amazon Web Services and other leading technology companies.

- Through its AI Apprenticeship Programme (AIAP)®,[67] AI Singapore aims to nurture the country's AI talent and expand job opportunities in AI-related fields. To apply, candidates must demonstrate a baseline skill set in data science and intermediate programming. Selected apprentices follow a two-month mentoring and self-directed learning scheme. Afterwards, they are assigned to AI Singapore projects (including 100E, mentioned above) for seven months to work on industry projects and thereby gain practical knowledge in building and deploying AI models. During this time, apprentices receive a training allowance ranging between SGD 3 500 and SGD 5 500 (EUR 2 500 and EUR 4 000). AI Singapore has also launched several training and instruction programmes[68] at various levels that address different audiences, including courses for students, educators, and workers. Some of these courses seek to increase the skills of prospective applicants to the AI Apprenticeship Programme.

*Information services and open-source code*

The AI diffusion mechanisms covered in prior sections aim to raise AI capabilities in firms. However, diffusion institutions can also support the development of standalone data platforms and open-source code that firms and other organisations can readily use to develop AI applications. For example, Mobility Data Space[69] is an online marketplace for automotive, transportation, logistics and many other types of data relevant to the mobility sector. It works as a data matchmaking service by providing a digital infrastructure for secure, peer-to-peer or one-to-many transactions. The data are exchanged for various purposes, including for companies to develop autonomous driving and mobility AI.[70] Data sellers can establish a price tag and define terms and conditions, such as the data's intended use, via technical and legal data usage policies.

Diffusion institutions frequently combine information services and open-source code with other mechanisms. For instance, the premise of Digital Catapult's Machine Intelligence Garage,[71] mentioned earlier, is to provide access to computational resources to assist early-stage AI start-ups. AI Singapore compiles and publishes various open-source tools developed through AI Apprenticeships and other programmes in its AI Ready Bricks[72] collection. Code is freely accessible to other AI engineers and companies and comes with information on use cases, tutorial videos, and other resources to help with reuse.

After developing proofs-of-concept through its AI Skunkworks programme, the NHS AI Lab publishes a working version of the related software code in a publicly accessible GitHub repository[73] under an open-source licence. This resource allows healthcare providers and companies supplying AI solutions to learn about the approaches undertaken with full technical details and reuse and build upon the code in their applications.

## Key barriers to AI adoption identified by diffusion institutions

In their day-to-day activities promoting AI, diffusion institutions have identified a series of obstacles that hinder adoption. These are described in the following sections.

### *Digitalisation is a necessary first step*

Before adopting AI, firms must embrace digital technologies that systematically gather data from business processes and customer and supplier interactions. AI applications need an accurate digital representation of business processes to make accurate predictions and prescriptions. However, many firms lag in adopting digital technologies. According to Sarah Gagnon-Turcotte, director of Forum IA Québec, "Adopting AI is the final step in organisations' digital technology adoption pipeline of 5-10 years, typically starting with Enterprise Resource Planning."

### *Insufficient understanding of AI*

Typically, companies that approach diffusion institutions have implemented some degree of digitalisation and have at least a superficial understanding of what AI is and what it can do for them. They generally recognise that AI can play an important role in their core business processes. Manufacturing and information and communication technology (ICT) firms have a general (though often limited) awareness of AI's potential benefits and applications. However, for other business sectors, use cases and applications are less clearly established, and as a consequence, investing in AI is perceived as too risky. In addition, firms that are capable of and interested in adopting AI tend to be concentrated geographically in regional clusters.

Even when firms have some familiarity with AI, managers often do not have a sufficient grasp of what AI is, what adoption entails, or what their businesses can gain from it. Managers are often confronted with the "black box" problem of AI, i.e. opacity in how the AI makes decisions or recommendations. They usually have a plug-and-play conception of adoption, i.e. they expect AI to be a commodity technology they can easily integrate into core business processes. Furthermore, technicians, whose training is based on understanding mechanisms and their workings, often believe that AI is unnecessary or does not offer value to their business. Given this insufficient understanding, managers and technicians can mistrust AI's predictions, recommendations or (even more so) decisions derived from the data.

### *ROI is difficult to estimate*

Companies must invest considerable time and resources to adopt each use case and tailor the AI application to their specific needs and conditions. Successful off-the-shelf solutions that firms can obtain from third parties are rare. To illustrate this point, Scale AI's Julien Billot compares AI today with "where the Internet was in 1995". Back then, setting up a website involved hiring specialised software engineers. Today, there are plenty of solutions for non-experts to build complex online portals.

Similarly, only a few third-party AI applications are currently available for firms. These applications allow companies to add AI features into Software-as-a-Service for generic use cases. "Companies try to buy AI applications as off-the-shelf licence-based solutions, only to find these do not work or only yield limited results," Valter Fraccaro and Riccardo Valletti from SAIHub point out. AI applications are generally ad hoc and subject to the firm's specific work environments and processes. Companies use diverse software and systems to manage business operations, production lines, services, accounting systems and other functions that need to be integrated when developing AI solutions. AI projects involve an important degree of experimentation, where the ROI is inherently uncertain. This happens even for well-established use cases.

AI applications need a proven record of success, especially regarding economic impacts, to convince firms to invest. Firms (particularly SMEs) that engage with diffusion institutions are often uncertain about what they can gain financially from implementing AI. They can find it challenging to define and delimit the business case for adoption. Companies often try to tackle complex problems with AI, making it difficult to estimate an ROI that might materialise several years later. Finding reliable estimates of the ROI can also be difficult, even when applications are narrowly defined. For instance, an ROI estimate in a predictive maintenance application relies on how well the counterfactual can be calculated. An AI system can, for example, alert users to the possibility of a machine breaking down, prompting a firm to service the machine for maintenance. But it is difficult to determine if this intervention was truly necessary and that the firm has indeed avoided a breakdown (with its ensuing costs). An historical record of breakdowns could help to estimate the ROI of such an AI system, but such data may not be readily available.

While it can sometimes be relatively straightforward to estimate cost savings and efficiency gains, it can be more challenging to calculate the ROI for new AI-enabled products, services or business models. Service providers selling AI solutions also face ROI-related problems, as the right revenue model can be unclear (e.g. subscription, licence, or charging per task as some cloud computing companies do). Different companies can use AI in many ways, making it hard for service providers to decide how to charge for it. Service providers are often uncertain about how companies will use their services. For example, some companies might use AI often and benefit from a subscription model. Other customers might prefer a pay-per-task model if their usage is sporadic.

### *A lack of access to AI skills*

Identifying, scoping and implementing AI applications requires a mix of technical and domain expertise involving employees with MSc or PhD diplomas. The presence of AI-skilled staff is often a baseline criterion for venture capital funds to invest in firms developing AI applications. However, as described in prior literature (see Chapter 2), diffusion institutions confirm that access to AI talent can be highly constrained, especially for SMEs. Smaller firms compete for limited AI specialists and data engineers with postgraduate education with large multinationals, including tech giants such as Amazon, Google and Microsoft, which can offer more attractive salaries and work conditions. SMEs also have more limited access to on-the-job training opportunities that can help staff build AI skills. Countries also compete for talent at the postgraduate level, e.g. by offering higher PhD salaries. Diffusion institutions often express regret that there are not enough AI-skilled students and graduates.

### *Insufficient data maturity*

Besides AI skills, diffusion institutions note a recurrent problem: firms often do not have the necessary data streams to develop AI applications. As mentioned above, data are essential to create, test, evaluate and validate AI models. However, companies approaching diffusion institutions for support often do not have sufficient data in terms of quantity, quality, cleanness and structure. They frequently lack an adequate understanding of what information needs to be gathered systematically. Consequently, they may not have the necessary data collection mechanisms in place or, if they do, struggle to assess how appropriate their data are for a given AI use case. Collecting high-quality data comes at a cost (which also needs to be factored into the ROI estimation). For instance, some manufacturing firms (particularly SMEs) may struggle to afford to install sensors in every factory, production line and machine they operate.

In addition to collecting the necessary data, firms also face data management challenges. They often have to be able to integrate data from different sources such as software, machines, business areas within the firm and data provided by third parties. Data sources can vary in periodicity (e.g. weekly, daily, hourly), type (e.g. quantitative or qualitative) and format (e.g. Excel spreadsheets, MySQL databases). Data can be unstructured, unlabelled and disorganised, making it challenging to integrate. Preparing data to build an AI model takes expertise and considerable time. According to AI Singapore's Laurence Liew, "Companies tend to underestimate efforts in getting data ready for AI applications." Companies can also struggle to access the necessary computing resources and cloud services. Deep learning, for example, is computationally expensive.

The data needed for AI applications can sometimes be outsourced, as automotive and transport sector companies do via the Mobility Data Space. However, data transfer and exchange also have obstacles. For instance, companies may have concerns about inadvertently selling personal data collected from customers (risk of data leaks[74]). For fear of losing the value of the data they collect, companies are sometimes unwilling to sell it or enter collaborative projects that exploit it. Data security (i.e. avoiding data breaches) and regulatory compliance are other emerging concerns when discussing data transactions. Some enterprises are reticent to publish data or the results from work with technology extension services or from funding for applied research. This aversion can make partnering with research institutions that manage such diffusion mechanisms difficult, as academics want to publish their research. Companies need to take this, and other researchers' needs and interests into account.

### *Uncertainties around regulatory compliance*

Diffusion institutions also confirm that firms struggle to navigate complex regulatory and ethical landscapes. Unaware of the applicable regulations and legislation, they often fear possibly unknown legal risks and inadvertently becoming non-compliant. Companies, and particularly SMEs, are often overwhelmed when dealing with existing and emerging regulations, such as the European Union's General Data Protection Regulation, as well as data acts and acts pertaining to AI. Managers often have questions about quality assurance requirements for AI applications and where liability lies if damage occurs to customers using AI-enabled products or services.

Insufficient knowledge of privacy regulations can make companies overprotective of data, rendering it challenging to explore and develop AI applications. Some diffusion institutions mentioned examples of drawn-out data-sharing requests for AI proofs-of-concept, which can take up to 12 months. Such a long wait time is excessive for start-ups and SMEs acting as AI service providers. The "black box" problem also means that biases in training data, breaches in regulation or ethical implications can go undetected unless the firm has specialised data engineers and staff trained in regulatory and ethical issues. Firms may hesitate to introduce new AI-enabled services or products, especially in public sectors like healthcare and education, due to uncertainties regarding how well the public will accept them.

### *Difficulties scaling up AI applications*

Many companies run proofs-of-concept without later deploying them as full-scale AI solutions, even if they were successful. An AI pilot application should be a milestone demonstrating the potential benefits of adoption. However, firms often run pilots without a strong vision or business plan to scale them up and integrate them with core business processes. According to diffusion institutions, firms often do not realise (or are unprepared to make) the shifts in organisational structure, business processes and culture needed to adopt AI solutions. Compared to adopting other digital technologies, adopting AI in core business processes can require a significantly larger company-level transformation, involving changes to business operations across various departments that managers lacking AI literacy often fail to foresee. "Large firms often misconceive AI as an add-on rather than a revolution," says Sarah Gagnon-Turcotte from Forum IA Québec. AI systems are not a one-off project. It is often the case that companies also fail to understand the extent of continuing investments required for AI quality management. Keeping AI models performing well over time requires constant assessment, retraining (with the most recent data) and redeployment.

Companies can also suffer from a "Not Invented Here" syndrome[75] when third parties are involved in developing AI applications. If insufficiently engaged or reassured, employees may refuse to co-operate, feeling anxiety about their jobs being made redundant by the AI system.[76] For example, one diffusion institution observed a case of internal pushback against a third-party application used in wholesale trade. In this instance, a new AI solution successfully predicted the demand for a company's product portfolio and performed better than its current system for projecting demand. However, deployment stagnated as the firm's information technology (IT) department defended its in-house system, raising conflicting interests in the company.

## Effective forms of support for AI adoption identified by diffusion institutions

Many of the approaches used to support the adoption of AI described in this chapter start with an early assessment of firms' digital and AI capabilities, e.g. addressed in the eligibility criteria for grants for business R&D, in technical visits that are a part of technology extension services and in workshops providing business advice. AI Singapore uses self-assessment tools to help companies evaluate their capabilities and determine the support they need. AI diffusion institutions usually select to work with firms with the right initial capabilities and where AI is or can be part of the company's core business. For companies that are not sufficiently digitally mature, many governments have a separate suite of policy instruments offering dedicated support for digitalisation.[77]

Various diffusion institutions report that they select only projects with a clear path to increases in performance, product or service quality, or cost reductions. They explain that this makes the achievement of tangible impacts in proofs-of-concept more likely, which helps to convince firms to scale up investments. Conversely, other institutions consider that firms should not obsess about the ROI from the outset and instead value experimentation that may lead to breakthroughs. In addition, other impacts might be sought besides raising productivity. Charles Huot from Cap Digital illustrates this point with the example of wind turbines equipped with cameras and AI to protect avian wildlife by autonomously reducing blade speed.

Diffusion institutions agree that catalogues of applications, use cases and success stories can help firms understand the possible gains from AI. Such catalogues help establish a proven record of success. They can also document experiences other businesses can learn from, such as what did not go well initially and how obstacles were overcome. In particular, case studies that measure the economic impact of investments (e.g. in terms of sales increases or cost reductions) can help tackle concerns around the ROI. In this way, catalogues can help managers better grasp the opportunities, challenges and limitations presented by AI. AI solution providers could also refer to such catalogues to better understand industry needs and adjust their service offerings. Some diffusion institutions included in this chapter are compiling such catalogues (Table 4.3).

### Table 4.3. Sample catalogues of AI applications, use cases and experiences

| Institution and web link | Short description |
|---|---|
| Digital Manufacturing and Cybersecurity Institute (MxD)<br>https://www.mxdusa.org/projects/ | A selection of past and ongoing projects funded by the Institute, including information on participants, problem statements, proposed solutions and impacts |
| Plattform Lernende Systeme<br>https://www.plattform-lernende-systeme.de/map-on-ai-map.html | A map covering AI applications that have been developed in Germany |
| Forum IA Québec<br>https://vitrine.ia.quebec/en/studies | A database of case studies of AI projects in the Quebec region |
| Fraunhofer IAO / IPA<br>https://www.ki-fortschrittszentrum.de/de/projekte.html | A database of over 70 case studies of publicly funded projects providing expert advice |
| NHS AI Lab<br>https://nhsx.github.io/skunkworks/ | A repository of projects supported by the NHS AI Lab |

Source: Authors.

Many factors driving the success of support for AI diffusion are specific to the type of mechanism used by diffusion institutions, as described in the following sections.

### *Technology extension services*

A recurrent point across the interviews is that companies should avoid thinking of AI as a technology in search of a solution. Instead, they should focus on delineating and describing their business problem and then assess the added value that AI might bring. Understanding the relevant opportunities offered by AI and properly framing the business problem provides the groundwork for determining what the company can gain from adoption, what data need to be collected, how data should be managed and how the AI model needs to be built. "As was the case for electricity in the early 20th century, AI won't be adopted for its own sake but for the innovations it enables," says Sarah Gagnon-Turcotte from Forum IA Québec.

In implementing technology extension services, the interviews suggest that diffusion institutions should work with firms following a sequence of steps:

1. establishing one or more business cases describing how to apply AI (for instance, clarifying how autonomous forecasting, decision support or decision making would help)
2. scoping possible AI solutions and assessing data maturity (for example, is the business gathering and processing the correct data?)
3. developing pathways to implementation.

Recommendations for each of these steps are presented below:

1. As mentioned earlier, use case analysis is a helpful tool to advance a base understanding of AI in firms. However, diffusion institutions need to actively link past experiences to firms' specific needs and culture. To establish a business case for AI adoption, diffusion institutions need to obtain as much operational data from firms as possible.
2. The staff of diffusion institutions need to spend time at the firm to assess its digital maturity and simulate what an AI solution would do. Proof-of-concepts should start by tackling more straightforward problems using readily available data. Staff should also estimate the ROI for a more extensive implementation project and help firms decide whether to invest in it. To this end, diffusion institutions highlight the need to have an economist join data engineers and other technical experts in technology extension projects.
3. An implementation roadmap should comprehensively describe what deploying the proof-of-concept as a fully integrated AI solution across the organisation entails. There are often significant impacts across various business processes and departments (e.g. accounting, purchasing and production). The roadmap should also describe how to ensure AI models perform well over time. The vision for implementation should be co-developed with staff from the outset to secure their co-operation.

Technology extension services reportedly work best when beneficiaries assign their own staff and contribute in-kind resources. Projects can also involve other types of actors (e.g. universities and research institutes). These collaborative projects can be valuable, particularly in pre-commercial stages involving AI applications that have not yet been introduced in any market. In various instances, diffusion institutions can offer technology extension services to multiple firms facing shared business problems.

### *Business advisory services*

According to interviewees, business advisory services can be particularly effective in three main ways. First, they can help firms make initial estimations of the ROI using scenario analysis without necessarily going into the technicalities of AI. For instance, advisors can help managers estimate the downtime of machines or production lines and the financial savings to be made using predictive maintenance. Second, diffusion institutions can help raise awareness and understanding of any public support for AI adoption offered at national and international levels (e.g. EU calls). Firms are often unaware of such support, including funding opportunities. Firms can also benefit from advisory services that help them prepare applications for assistance and maximise their chances of obtaining a favourable response. Third, diffusion institutions can offer business advisory workshops to raise AI literacy in managers. They can also provide advice on ethics and regulation.

### *Networking and collaborative platforms*

Similarities often exist in companies' business problems and how they use AI to solve them. Seminars and conferences can facilitate exchanges between business executives and help raise understanding of the opportunities AI presents and the types of transformation that firms need to make. Seminars and conferences also facilitate networking between managers, researchers, trade associations, diffusion institutions, AI solution providers and other actors. Such events can help AI reach business sectors where adoption tends to be lower. Furthermore, they can systematically gather the views of stakeholders in order to inform and shape policies and regulations for AI.

### *Grants for business R&D and applied public research*

Financial support reduces the risks entailed in developing proofs-of-concept and exploring theoretical applications. Some grant schemes ask firms to indicate the expected ROI or cost reduction in their funding application as part of their allocation criteria. Diffusion institutions can provide guidance in this connection. For example, they can help businesses estimate savings and sales projections. They can also keep track of such estimates and see if they materialise over time. Financial support can also help firms build a digital infrastructure for collecting, managing, and processing data for AI, e.g. support for deploying IoT technologies. Some business sectors, such as adtech and fintech, already use AI intensively. However, when used to help acquire third-party AI applications, grants can encourage other business sectors to work with AI solution providers. According to the interviewed diffusion institutions, grants that deliver the best outcomes require beneficiaries to match public support with their own resources (financial or in-kind). Similarly, publicly funded research projects produce the best results when companies assign their staff to the research team.

### *On-the-job training*

Training courses are essential for existing employees to gain the technical knowledge required for AI adoption. Tools for self-assessment of digital maturity, like AI Singapore's AI Readiness Index, can also be used as training tools for managers, venture capitalists and solution providers to learn to identify use cases and design business models for AI solutions. Managers and technicians can also be trained in information governance, regulations and ethical issues. Such training can help tackle compliance and AI assurance concerns that often stop firms from using their data or prevent them from engaging with AI altogether. While on-the-job training can help firms address the scarcity of workforce skills in AI in the short term, various diffusion institutions are of the view that countries need to step up efforts in embedding AI across tertiary education.

### *Information services and open-source code*

Open-source tools make AI methods and resources accessible to a broad audience beyond AI specialists and computer scientists. Statisticians, data engineers, physicists, and other professionals with varied backgrounds can work more readily with such tools than by developing algorithms from scratch. Diffusion institutions use open-source resources together with other mechanisms, such as on-the-job training and technology extension services (AI Singapore and NHS AI Lab).

Publicly funded infrastructures that subsidise computing resources (e.g. hardware or computation credits on the cloud) and provide real or synthetic training data for free or at a low cost can be particularly helpful for SMEs. Such resources also need to be combined with other forms of support, such as business advice. For example, Digital Catapult's Machine Intelligence Garage, described earlier, gives SMEs access to computational resources in combination with mentorship and fundraising opportunities. By verifying the parties' identities and ensuring the integrity of data transfer, digital platforms and online marketplaces provide a trustworthy channel for secure data transfers. According to Moritz Stober (acatech – National Academy of Science and Engineering), firms tend to underestimate the opportunities to establish data partnerships to tackle common problems, especially those involving competitors.

## Conclusion

This chapter reports findings from structured interviews with 19 institutions across the G7 countries and Singapore that work to increase the uptake of AI. It has not sought to establish a comprehensive picture of the entire institutional landscape supporting AI adoption across these countries. Rather, it samples and characterises diffusion mechanisms and gathers institutions' views on the main barriers to the adoption of AI in firms and the most effective forms of support for adoption. Future work could use this chapter's findings to survey a larger number of institutions supporting AI adoption.

The diffusion institutions interviewed for this chapter confirm the obstacles identified in prior literature. They emphasise uncertainty over the ROI as a critical obstacle for firms considering adopting AI. Managers often struggle to grasp how AI can solve real problems in the workplace. They also tend to underestimate the implications of deploying AI solutions, which often involve significant changes in business culture and processes across many (if not all) parts of the firm. A lack of AI skills and data maturity are fundamental barriers to implementing AI. Moreover, uncertainties about regulation can prevent firms from taking steps towards adoption.

This chapter identified seven main mechanisms that diffusion institutions use to help firms overcome the challenges of adoption.

1. **Technology extension services** can help firms delineate and define the business problem to be solved and develop proofs-of-concept that demonstrate how AI can help.
2. **Grants for business R&D** remove part of the risk associated with AI investments.
3. **Business advisory services** provide non-technical assistance that can raise managers' understanding of their firms' AI readiness and the specific opportunities and challenges that AI entails.
4. **Grants for applied public research** which can help promote high-risk research and/or the development and implementation of technologies close to commercialisation.
5. **Networking and collaborative platforms** help build AI ecosystems of public and private actors, creating demonstration effects and opportunities for knowledge transfer.
6. **On-the-job training** can help address bottlenecks around AI skills.
7. **Information services and open-source code** provide helpful resources for firms seeking to strengthen their AI capabilities.

Diffusion institutions often combine these mechanisms to optimise their impact (see Box 4.2).

### Box 4.2. Synergies across AI Singapore's programmes

AI Singapore's "AI for industry" training courses are structured to prepare professionals for the AI Apprenticeship Programme. Apprentices, in turn, are embedded in other programmes (e.g. 100E, AI Ready Bricks). The results from R&D supported by AI Singapore are available for firms to adopt and extend through collaboration and licensing opportunities.

AI Singapore selects highly motivated and self-directed individuals who have already independently acquired data science and AI skills. This selection of candidates who already possess skills but lack real-world experience allows them to give the apprentices two months of deep skilling, after which they can put them to work on a hands-on project within a team. In AI Singapore's 100E programme, companies invest up to SGD 180 000 (30% cash, 70% in-kind) to implement a project with visible ROI and deployment as the objective. AI Singapore matches the contribution in kind with AI engineering resources (for a total of SGD 360 000), ensuring commitment on both sides. The programme is designed for companies to derive tangible benefits, including AI models that can be deployed nearly immediately into production for an immediate ROI.

While they would like to help every Singaporean and every Singaporean company, they cannot do so. So, they use the AI Readiness Index to identify and work only with AI-ready companies. For companies that are AI-unaware or AI-aware or individuals who are not ready for the apprenticeship, they point them to other programmes. This way, they avoid over-taxing their team in trying to help everyone or every company that comes to them.

Source: Liew (2024[6]).

While diffusion institutions have developed sophisticated mechanisms tailored to AI technology adoption, they can only support a small fraction of the population of firms that could benefit from AI. The number of firms these institutions serve tends to range between 10 and 400 annually, depending on the diffusion mechanism.[78] The relatively limited scale of the public AI diffusion mechanisms considered here contrasts with the ambitious scope of national strategies and aspirations for the widespread adoption of AI that governments from the G7 countries and beyond have laid out.

Policy makers also have to consider the additionality of impacts from their spending – that is, evaluating outcomes compared to what would have occurred without public support. As noted earlier, firms often self-select into programmes offered by diffusion institutions, raising the question of whether these firms might have eventually adopted AI through other channels. Currently, there is no evidence that this possibility has been tested rigorously. Further research could measure the additionality achieved by diffusion institutions, including the magnitude of demonstration (or spillover) effects. One approach might involve identifying control groups of firms similar to those receiving support at the time when successful candidates are accepted into programmes. A more elaborate method could involve randomised control trials. While such research may be costly, the expense might be justified if policy makers intend to expand these diffusion programmes significantly.

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Sargent, J. (2019), *The Manufacturing Extension Partnership program*, Congressional Research Service, https://catalog.libraries.psu.edu/catalog/30866457. [4]

## Notes

[1] For instance, the US-based Hollings Manufacturing Extension Partnership (MEP), one of the diffusion institutions studied in this chapter, estimates that for every dollar of public investment, the programme generates USD 26.20 in new sales growth and USD 34.50 in new investment in the supported firms (MEP, 2020[8]).

[2] The OECD AI Observatory can be accessed at https://oecd.ai/.

[3] The Science, Technology and Innovation Policy Compass can be accessed at https://stip.oecd.org.

[4] For a survey on the activities, governance and funding modalities of RTOs, see Larrue and Strauka (2022[7]).

[5] See Fraunhofer Institute for Industrial Engineering IAO at www.iao.fraunhofer.de/en/about-us/fraunhofer-iao.html.

[6] Author's communication with Fraunhofer IAO staff, 28 April 2022.

[7] More information about the Fraunhofer Institute for Manufacturing Engineering and Automation IPA can be found at www.ipa.fraunhofer.de/en/about-us/institute-profile.html.

[8] The AI Innovation Centre's homepage is located at www.ki-fortschrittszentrum.de/en.html.

[9] More information about this service is available at www.iao.fraunhofer.de/en/press-and-media/latest-news/expert-advice-on-getting-started-in-AI-and-robotics.html.

[10] See Vector Institute's About page at https://vectorinstitute.ai/about.

[11] More information about the FastLane Program is available at https://vectorinstitute.ai/fastlane-program.

[12] See MEP-Assisted Technology and Technical Resource (MATTR) at www.nist.gov/mep/mattr.

[13] AIRI's homepage is located at www.airi.unimore.it.

[14] Author's communication with AIRI staff, 2 August 2022.

[15] See NHS AI Lab's website at https://transform.england.nhs.uk/ai-lab.

[16] See Digital Catapult's About page at www.digicatapult.org.uk/about.

[17] Author's communication with Digital Catapult staff, 10 May 2022.

[18] More information about the accelerator is available at https://accelerator.madesmarter.uk.

[19] Scale AI's website is located at www.scaleai.ca.

[20] Other Global Innovation Clusters focus on digital technologies, protein industries, advanced manufacturing and the ocean economy. See https://ised-isde.canada.ca/site/global-innovation-clusters/en.

[21] More information on these projects can be found at www.scaleai.ca/projects.

[22] See MxD's website at www.mxdusa.org.

[23] Manufacturing USA's portal can be accessed at www.manufacturingusa.com.

[24] More information on these projects can be found at www.mxdusa.org/projects.

[25] Author's communication with MxD staff, 27 May 2022.

[26] See NEDO's website at www.nedo.go.jp/english.

[27] See the programme page at www.nedo.go.jp/english/activities/activities_ZZJP_100138.html.

[28] See the programme page at www.nedo.go.jp/english/activities/activities_ZZJP_100137.html.

[29] The Ministry provides more information at https://greentechinnovation.fr/les-acteurs-de-lia.

[30] Smaller firms have a higher share of public support.

[31] More information on this programme is available at https://s.fhg.de/KI-Fortschrittszentrum-AI-Innovation-Seed.

[32] See AI in Health and Care Award at https://transform.england.nhs.uk/ai-lab/ai-lab-programmes/ai-health-and-care-award.

[33] AI Singapore's website is available at https://aisingapore.org.

[34] Besides AI diffusion, AI Singapore also supports basic research that can advance strategic technologies and address societal challenges (see, e.g. AI Governance Research Grant Call, AI Research Grant Call, and AI Kickstarter Grant Call).

[35] More information about this programme is available at https://aisingapore.org/industryinnovation/100e.

[36] See Cap Digital's About page at www.capdigital.com/en/who-we-are/our-mission .

[37] Author's communication with Cap Digital staff, 11 April 2022.

[38] See Machine Intelligence Garage at https://migarage.digicatapult.org.uk.

[39] See Scale AI's AI Acceleration programme at www.scaleai.ca/acceleration.

[40] See www.scaleai.ca/acceleration/the-programs-were-investing-in.

[41] More information on this partnership can be found at https://uwaterloo.ca/news/university-relations/waterloo-and-nrc-reaffirm-partnership-future-facing.

[42] Author's communication with NRC staff, 12 August 2022.

[43] See DFKI's website at www.dfki.de/en/web.

[44] Author's communication with DFKI staff, 26 July 2022.

[45] See the programme website at www.nedo.go.jp/english/activities/ZZCD_100016.html.

[46] See the programme website at www.nedo.go.jp/english/activities/activities_ZZJP_100194.html.

[47] See the programme website at https://aisingapore.org/grand-challenges.

[48] See the programme website at https://aisingapore.org/technology/technology-challenges.

[49] See the programme website at https://aisingapore.org/innovation/technology-offers.

[50] SAIHub's About page is available at https://saihub.org/service/missionevision.

[51] These prizes are described at www.quinewssiena.it/siena-programma-stayhub-assegnati-premi-studenti.htm (in Italian).

[52] Author's communication with SAIHub staff, 2 May 2022.

[53] See Forum IA Québec's website at https://forumia.quebec/en.

[54] This directory is available at https://vitrine.ia.quebec/en/directory.

[55] Plattform Lernende Systeme's homepage is at www.plattform-lernende-systeme.de/home-en.html.

[56] The Map can be accessed at www.plattform-lernende-systeme.de/map-on-ai-map.html.

[57] See techUK's About page www.techuk.org/who-we-are/about-us.html.

[58] More information on this service can be accessed at www.nist.gov/mep/supplier-scouting.

[59] See Scale AI's events at www.scaleai.ca/events.

[60] The web portal is available at https://epoch.aisingapore.org.

[61] See Vector Institute's training courses at https://vectorinstitute.ai/programs-courses.

[62] For more information on these internships, see https://vectorinstitute.ai/internships.

[63] For North Carolina MEP, see https://ncmep.org/lean-helping-small-manufacturers-test-artificial-intelligence. Information on South Carolina MEP is available at www.scmep-online.org/courses/introduction-to-machine-learning-and-artificial-intelligence.

[64] See Scale AI's partner training programmes at www.scaleai.ca/education/individuals.

[65] See Scale AI's training courses at www.scaleai.ca/training/businesses-how-to-apply-for-funding.

[66] More information on the Virtual Training Centre is available at www.mxdusa.org/vtc.

[67] See the programme website at https://aisingapore.org/industryinnovation/aiap.

[68] Information on these programmes is available at https://learn.aisingapore.org.

[69] See Mobility Data Space at https://mobility-dataspace.eu.

[70] Author's communication with Mobility Data Space staff, 29 August 2022.

[71] See the programme website at https://migarage.digicatapult.org.uk.

[72] These resources are available at https://aisingapore.org/aiproducts/ai-ready-bricks.

[73] This repository can be accessed at https://nhsx.github.io/skunkworks.

[74] Unauthorised data transmission to a third party may happen in various ways, such as through file transfers or unlawful system access (hacking).

[75] The "Not Invented Here" syndrome refers to the tendency to avoid ideas, services, products or business solutions developed outside the organisation.

[76] Several diffusions institutions indicated that adopting AI generally does not lead to staff layoffs. Rather, AI systems often free up employees to engage in more productive work.

[77] For an overview of policies supporting the adoption of digital technologies, see www.youtube.com/watch?v=xwAtBd40pSQ.

[78] Some diffusion mechanisms are more resource-intensive than others. For example, institutions that deliver technology extension services or grants for applied public research tend to work with fewer firms per year compared to those hosting networking and collaborative platforms.

# 5 Findings from interviews with firms adopting artificial intelligence

This chapter reports the findings of interviews with senior staff responsible for artificial intelligence in firms in the two sectors addressed in the 2022-23 OECD/Boston Consulting Group/INSEAD survey. The interviews aimed to elicit qualitative information to better interpret the quantitative data gathered through the survey, particularly in terms of policy-relevant questions considered novel in the context of other international surveys.

## Introduction

Artificial intelligence (AI) could transform industries across the globe, prompting a need for in-depth understanding of its adoption and impact. This chapter presents findings from a series of interviews conducted with senior staff responsible for AI in firms from manufacturing and information and communication technology (ICT) services. These interviews complement and provide qualitative context to the quantitative data gathered through the 2022-23 OECD/BCG/INSEAD survey, offering insights into a range of policy-relevant questions.

The interview process involved 15 experts holding various high-level positions, including chief information officers, chief technology officers, heads of digital business, directors of digital transformation, a vice president of data science and data engineering, data and machine learning engineers, and heads of research and development (R&D), among others. Some interviewees were drawn from enterprises that participated in the survey, while others were selected from a pool of over 600 candidates. The selection ensured approximately equal representation among countries and the two surveyed sectors.

The interviews focused on three primary themes:

1. **Data acquisition**: This theme explored how companies acquire data, with particular emphasis on data from research institutes and the public sector.
2. **Public services to support AI adoption**: The interviews sought to understand how companies interact with public services to develop AI and the key challenges they face in this process.
3. **External collaboration for AI development**: This area investigated practices for better AI adoption by leveraging the broader ecosystem, including suppliers and academic and research institutions.

The remainder of this chapter is structured to provide a comprehensive account of the findings. The following three sections summarise the salient insights gathered for each of the above topic areas. The chapter presents possible policy implications derived from these insights throughout the sections, summarising them in the conclusion.

## Data acquisition

The interviews revealed that while many enterprises acquire data from research institutes and the public sector and recognise the many initiatives taken by governments in this connection, most rely on private data sources. The most common type of data acquired from public sources is generic data, such as demographic information, public company records, labour statistics and weather data. More specific and commercially valuable data sets from public administrations are rare. Private data sources are the preferred choice for most firms, as they offer more specialised and proprietary data that can provide competitive advantage. In addition, there may be more opportunities for giving feedback on data quality to private providers of data than to public providers.

Interviewees indicated that procedural complexities in acquiring public data significantly impede data-driven decision making. These complexities, deeply rooted in administrative processes, often exist to ensure accountability and adherence to established protocols. While such attributes are essential for maintaining data integrity and security, they often come at the expense of efficiency. Multiple layers of approvals, reviews and checks can lead to prolonged waiting periods. One expert observed that permissions can take up to six months or longer. Such delays can render data obsolete when accessed.

Interviewees noted that data from public repositories is often too old for real-time applications. Many businesses must invest time and effort to validate the currency of public data. Many types of data can quickly become outdated due to rapid technological changes and evolving market dynamics, among other conditions. Policy makers need to ensure that data remains relevant and actionable in the face of constant change.

Beyond timeliness, many interviewees expressed concern about data quality. Using publicly sourced datasets is often problematic due to vague terminologies and other shortcomings. The absence of comprehensive documentation can leave users grappling with the data's true meaning and context. For example, a business might come across a large comma-separated values (CSV) or Excel file from a public source and encounter columns filled with terminology that is not easily understandable, while lacking accompanying documentation for clarification. A common problem the interviewees reported is the data quality itself. For example, it is not uncommon to encounter discrepancies, conflicting information and missing data. Considerable work is often needed on data cleaning and preparation, even for data that require a fee. Some interviewees noted that data obtained from public sources is of lower quality than that obtained from private sources. Overall, policy makers need to ensure that any shortcomings in data quality described here are addressed.

There is also a need for comprehensive documentation and standardised application processing interfaces (APIs). Comprehensive documentation serves as a roadmap for developers, guiding them through the intricacies of the data and helping to integrate it into their systems. Interviewees observed that it is essential that when querying an API, the results align with expectations and that any anomalies or potential quality issues are clearly explained. Moreover, adhering to standard practices ensures compatibility with existing technologies used to develop applications, such as REST API (Representational State Transfer), which is a set of rules and conventions for building and interacting with web services. Such standards streamline the integration process and bolster security and reliability.

A centralised public sector data access platform could streamline the search and retrieval process. A centralised hub could aggregate data and facilitate seamless transitions between databases, enhancing users' ability to access and link to specific studies or datasets. Interviewees underscored that the absence of a unified platform often complicates data discovery.

Further, interviewees considered that the legal frameworks governing cross-border data flows could be made more compatible. International data sharing can be an intricate process, particularly when navigating diverse data-sharing laws. Different countries have distinct data protection and privacy laws. For instance, the European Union's General Data Protection Regulation (GDPR) is one of the most stringent frameworks globally. Regulations along the lines of GDPR can facilitate data sharing as they support standardisation and trust. However, other jurisdictions might have more lenient or different standards. This can pose challenges for companies that operate in multiple jurisdictions and need to comply with each region's specific regulations. To utilise data from different countries, specific protocols must be established to define how the data can be used, whether it can be merged, and under what conditions it can be combined.

Finally, vendor certification is common across industries and could be adapted for data vendors. One interviewee noted that such certification would help to provide assurance and confidence in the data's authenticity and reliability. Especially for small and medium-sized enterprises (SMEs), checklists of the most important criteria to consider in vendor search and selection would be helpful.

## Public services to support AI adoption

### *Access to information or advice concerning the adoption of AI*

The survey data show that 75% of responding enterprises in manufacturing and 69% in ICT utilise public services that offer information and guidance pertaining to AI adoption (see Chapter 3). Most interviewed experts affirm that the insights derived from public sector sources help to make informed decisions and shape business strategies. Companies acknowledge the challenges of staying well-informed about markets beyond their own expertise. Access to information such as economic data, regulatory updates and compliance guidance is considered valuable. Such information is crucial in planning, analytics, market sizing, go-to-market strategies and understanding market dynamics.

Interviewees drew attention to a lack of consolidated information on private-sector AI software or services. Companies frequently receive tailored use case solicitations from vendors. These are often presented in marketing language. One interviewee suggested that governments could help by providing such information but in more neutral ways. One measure could involve providing information on solution providers with a relevant industry-specific track record. A suggestion made by some interviewees was that governments could facilitate decision making for businesses seeking AI solutions – especially SMEs – by developing a preferred vendor list, particularly for companies facing regulatory compliance considerations. Such a list would offer a curated selection of vendors with proven expertise in specific industries. This approach – aimed at reducing firms' search costs for valuable advice – has been adopted by Singapore's national research and innovation programme to harness AI's scientific and economic potential (AI Singapore).

However, other interviewees expressed reservations about this idea, especially as concerns the possible anti-competitive effect of public authorities indicating private-sector contracting preferences. They suggested that governments could adopt an alternative approach of providing guidelines or a framework to aid SMEs in navigating the vendor selection process. By advising them on, for instance, the top ten considerations to bear in mind when choosing an AI vendor, governments could assist firms without favouring specific vendors. This would help firms evaluate AI products or services while preserving their autonomy in making vendor choices.

Interviewees also pointed to challenges in accessing public sector information to facilitate AI development. They highlighted the frequent lack of clear pathways to specific public agencies. The absence of a one-stop interface and streamlined processes and the occasional fragmentation of channels to public services create challenges to identifying the right agency or programme to consult. Interviewees highlighted that policy makers could help by establishing a consolidated platform or resource hub that streamlines access to AI-related information, guidance and advice from public agencies. Especially for SMEs, this would alleviate the burden of navigating fragmented services and help ensure transparency. Guidelines outlining agency roles and expertise, along with mechanisms for companies to communicate their needs, would also enable more targeted and efficient exchanges. Some interviewees emphasised the importance of having a single point of contact to assist in using various public support initiatives. Where this had occurred, having a dedicated contact person had proved highly beneficial.

Some ICT services companies do not consider public agencies an important source of guidance on AI development. These companies often deeply understand AI and possess internal capabilities to effectively drive their AI initiatives. As a result, they tend to rely less on external sources for direction and guidance. They are generally confident in their ability to chart their own course and make informed decisions based on in-house expertise.

### *Publicly provided or supported training services*

The survey data reveal that approximately 58% of enterprises in the sample use public sector training services to help adopt AI (see Chapter 3). Regardless of sector, all interviewees reported challenges in finding AI talent. For instance, in manufacturing, companies seeking to implement AI-driven automation or predictive maintenance often struggle to find skilled professionals with expertise in AI algorithms, machine learning and data analysis. Similarly, in the ICT services sector, companies specialising in AI software development, natural language processing or computer vision encounter difficulties finding qualified professionals with specialised AI knowledge. This scarcity of talent hinders innovation and the deployment of cutting-edge AI solutions.

Those interviewees who expressed a reluctance to use public sector training programmes emphasised the need for more specificity in the training offered. For instance, instead of generic AI training, they found greater value in programmes tailored to industry or business-specific needs. For example, manufacturers may prefer training in AI that focuses on optimising supply chain management, while healthcare companies may seek training on AI applications for medical diagnostics.

Additionally, the experts highlighted the importance of hands-on training oriented towards real-world projects. Programmes that incorporate practical exercises and projects help participants to better apply AI concepts in the workplace. Workshops in which participants use AI tools and datasets related to their industry can be highly effective in boosting readiness to adopt AI.

Various interviewees asserted that public sector providers should collaborate with industry to deliver targeted training. Inviting industry professionals to share their experiences and insights can help develop training materials that provide practical perspectives and reflect best practices that resonate with private companies. The interviewees considered that collaborations between the public and private sectors can contribute to training programmes' overall efficacy and appeal.

While companies welcome public initiatives to develop human capital, the relevance of these varies depending on companies' industry and size. Among the experts interviewed, manufacturers more frequently expressed the need for new qualification frameworks. In line with the survey findings, the interviewees reported that some companies face challenges in determining the specific AI skills they need. Often, AI is perceived as a broad, all-encompassing term, overlooking the existence of distinct subfields within it. This contributes to a problem where academic certifications may not sufficiently provide the comprehensive information that employers seek. In this rapidly evolving field, there is a growing need for new qualification frameworks that effectively communicate precise and relevant information regarding candidates' capabilities and competencies to employers.

The interviewed experts agreed on the need to develop new AI curricula to meet the growing demand for skilled AI professionals. During the interviews, experts provided insights on the content of AI degree programmes and perceived gaps in curricula. Many held that AI degree programmes lack a sufficient focus on industry-specific applications and practical skills. For example, a manufacturing company might require AI professionals with expertise in optimising production processes through AI-driven automation, while a healthcare organisation may seek AI graduates who are well-versed in medical image analysis and diagnosis. The experts highlighted the importance of gaining hands-on experience as a part of degrees in AI. Companies often seek AI professionals who can immediately apply their knowledge to real-world scenarios. Hence, curricula that incorporate practical components, such as internships or industry placements, are highly valued by employers.

Experts also expressed concern about the limited pool of AI graduates possessing specialised skills in subdomains of AI. The rapid expansion of AI has resulted in a scarcity of professionals equipped with the latest expertise in AI systems and applications. To tackle this challenge, certain companies have launched talent development initiatives. These initiatives include sponsoring AI-focused research projects and providing scholarships to students pursuing AI degrees. For instance, a data analytics firm might offer scholarships to students pursuing a master's degree in AI with a focus on natural language processing, aligning with the company's core business. Training efforts should also extend beyond individuals in technical roles. They should also include educational and training opportunities for individuals from diverse backgrounds and fields of expertise outside AI.

### *Publicly provided or supported funding programmes*

The survey showed that 42% of enterprises use services provided by the public sector to promote access to finance, including subsidies and credit guarantees (see Chapter 3). It became evident during the interviews that many companies display a high level of awareness regarding the types of available public funding to support their AI initiatives. They demonstrate a clear understanding of the various avenues for financial assistance, such as tax credits, public funding for R&D, subsidies from public investment banks, and financing options guaranteed by the state. Among these forms of support, tax credits were the most frequently utilised.

In the 2022-23 OECD/BCG/INSEAD survey, around 40% of enterprises reported that their utilisation of AI in the past 12 months was constrained due to a lack of external financing (see Chapter 3). Interviewees emphasised that the evaluation methods for securing public funding can be overly narrow. The main issue is that the assessment processes for obtaining public funding, particularly grants, often focus on individual projects rather than a broader range of projects. Assessing projects individually increases the risk of failure for lending programmes overall, especially given the inherent complexities and uncertainties in the emerging field of AI. This funding may also fail to capture the collective impact and transformative potential achievable through a portfolio of AI projects in a company.

Some experts also underscored the importance of streamlining application processes for public funding. Doing so would give reviewers more time to study a project's merits and, moreover, support SMEs that may otherwise struggle with complex application procedures.

## External collaboration for AI development

### *Engaging with universities and public research institutions to develop AI*

The OECD/BCG/INSEAD survey showed that collaboration with universities and public research institutions is widespread. More than half of the responding enterprises collaborate with university faculty members, PhD candidates or postdoctoral students to advance AI development. Approximately 55% of manufacturers and 48% of ICT services providers collaborate with researchers in public research organisations. In addition, around one-third of enterprises form partnerships with undergraduate students to foster AI innovation and research (see Chapter 3).

Collaboration with universities and public research institutes improves access to scientific expertise. Academic research institutions house highly skilled researchers and domain experts. By collaborating with these institutions, firms tap into expertise and opportunities for cutting-edge research that may not be readily available within their own organisations. This access to specialised knowledge helps firms address complex AI challenges more effectively.

The interviews showed that collaborative partnerships can facilitate knowledge exchange and technology transfer between firms and academic institutions. Firms can share their industry insights, practical experience and real-world datasets, enriching academic research. In a complementary way, academic institutions can share their latest research findings, methodologies, and theoretical advances, helping firms to leverage cutting-edge research. These partnerships can also provide access to state-of-the-art research facilities, advanced computing infrastructure and dedicated R&D teams, enabling firms to undertake more ambitious and resource-intensive AI projects.

Collaborating with academic research institutions provides firms with opportunities for talent acquisition and development. By engaging with PhD students, researchers and faculty, firms can identify and recruit talent. Furthermore, these partnerships facilitate internships and joint training programmes that help nurture the next generation of AI professionals in academia and industry.

The interviews suggest that firms often struggle with a lack of clear agreements and frameworks for intellectual property (IP) management and ownership. Collaborations between research institutions and firms, especially those in the ICT services sector, frequently yield intellectual property and the associated IP rights. The interviewees noted that striking a balance between the interests of both parties regarding the ownership, usage and commercialisation of IP can be complex and may give rise to disagreements.

Indeed, naturally, firms often focus on commercialisation and return on investment, while academic institutions prioritise scientific discovery, publication and academic recognition. These differing goals and incentives can lead to conflicts in terms of confidentiality and data sharing. One interviewed expert highlighted the potential benefits of developing framework or model non-disclosure agreements to facilitate collaboration between firms and universities.

Challenges around IP tend to be more prominent among ICT services companies. There are several possible reasons for this. First, the ICT services sector is a source of particularly rapid advances and innovations in AI, entailing frequent and significant developments in software, algorithms and digital technologies. These advances can lead to complex and rapidly evolving IP landscapes, making it more challenging to establish agreements and frameworks for IP management. Second, ICT services companies heavily rely on intangible assets such as software, algorithms, patents and copyrights, which are more difficult to protect and manage than tangible assets. The intangible nature of these assets makes it harder to establish ownership, usage rights and commercialisation agreements, potentially leading to disagreements.

Firms and universities often experience difficulties with respect to cultural and organisational differences. Most interviewees drew attention to the complexity of managing the distinct cultures, priorities and operational structures characteristic of corporate and academic environments. These diverse institutions typically have different approaches to decision making and timelines. The interviewed experts emphasise that academic institutions often operate on longer-term research cycles, while firms operate in fast-paced, market-driven environments. This disparity in timelines can pose challenges in terms of project co-ordination, responsiveness to market demands and the ability to adapt quickly.

Lack of transparency in funding mechanisms and project governance in industry-university collaborations appears to be a roadblock. The interviewed experts emphasised the importance of establishing sustainable partnership models to foster enduring collaborations with academic research institutions. Other obstacles mentioned in some interviews were the lack of transparency in how the funding firms provide is used, how other developments within universities might affect a project (such as a turnover in postdocs) and overall project governance. Interviewees reported uncertainties in terms of funding allocation and accountability. The absence of clear guidelines, transparent processes and well-defined project governance structures can impede the smooth operation of collaborative projects and create a lack of clarity regarding roles and responsibilities, leading to delays, misunderstandings and even conflict.

Collaborative schemes tailored to the needs of SMEs help with the adoption of AI. One interviewee highlighted that centres of AI research predominantly focus on collaborations with medium and large-sized enterprises. At least in some locations, dedicated SME-focused programmes are scarce. Specialised programmes tailored to SMEs' requirements could unlock a myriad of advantages. SME-specific collaborative schemes would allow smaller businesses to bring their data science problems to the table while gaining access to needed AI research and expertise. Dedicated programmes could help address specific challenges faced by smaller businesses, such as overall resource constraints and more limited access to AI talent.

Interviewees held that financial support for collaborations could help. The interviewed experts expressed concerns about their shouldering most of the financial risk when they sponsor academic research programmes. Given the inherent uncertainties and sometimes high costs associated with AI development (particularly as regards human expertise), the experts generally believed that public financial support would help to mitigate risk. That public financial support could be prioritised for enterprises' first collaborative experience.

Companies would like less complex processes when applying for public funds to support AI research in collaboration with universities. Simplification and a lower administrative burden would make application more efficient. Interviewees also stressed the importance of enhancing transparency throughout the process. Clear guidelines, well-defined evaluation criteria, practical examples of successful applications, and accessible information about funding opportunities would help companies better understand expectations and requirements. Additionally, interviewees advocated for feedback loops that facilitate communication between funding agencies and applicants. This would help companies learn from previous experiences and increase future success rates.

## Conclusion

In conclusion, the interviews with senior staff from enterprises in the manufacturing and ICT services sectors have provided valuable insights that can help inform policy makers in shaping effective strategies for AI adoption and development. The challenges and opportunities identified in data acquisition underscore the importance of streamlining access to public sector data. Policy makers can play a crucial role in establishing centralised platforms, standardised APIs, and cross-border data-sharing frameworks to enhance the quality, timeliness and accessibility of public data. Addressing procedural complexities and ensuring data relevance are essential considerations for policy makers seeking to foster a conducive environment for data-driven decision making in firms.

The findings related to other public services supporting AI adoption emphasise the need for more transparent, industry-specific information and guidance. Policy makers can explore options such as developing guidelines for vendor selection, especially for SMEs. Efforts to streamline application processes for public funding and enhance transparency can help address the financial constraints reported by enterprises, fostering a more supportive ecosystem for AI initiatives. Policy makers should also consider the industry-specific training needs highlighted by interviewees and bear in mind the potential for further development of curricula, as well as the importance of hands-on, work-based training and collaboration between public and private sectors in bridging talent gaps.

Finally, interviewees highlighted the importance of clear agreements, frameworks and funding mechanisms in industry-university partnerships. Policy makers could contribute by facilitating the development of standardised non-disclosure agreements and sustainable partnership models between universities, public research organisations and firms, particularly addressing the needs of SMEs. As regards financial support, simplified application processes and improved transparency in the evaluation criteria could help. Financial incentives could also encourage collaborations between enterprises and academic institutions and might focus on incentivising the first collaboration experience.

In summary, the interviews underscore the multifaceted nature of challenges and opportunities in AI adoption, providing policy makers with a nuanced understanding to help craft informed and effective policies.

# 6 Survey of artificial intelligence in the state of São Paulo, Brazil

This chapter reports the results of a survey of artificial intelligence (AI) in enterprises in the state of São Paulo – the most economically important state of Brazil – using the same OECD/BCG/INSEAD survey questionnaire administered to 840 enterprises in the Group of Seven (G7) countries in 2022-23. This chapter aims to present new data on AI use in firms in Brazil and compare these results to the findings from the OECD/BCG/INSEAD survey presented in Chapter 3. Overall, the use of AI is limited in the state of São Paulo, and there is a low incidence of enterprises developing AI systems internally. Benefits could come from examining the suitability of current funding and other support mechanisms.

## Introduction

São Paulo is the most populous state in Brazil. In the most recent population census (2022), the state had 44.4 million residents, almost 22% of the population of Brazil.[1] Economically, the state of São Paulo is also the largest, accounting for around 31% of Brazil's gross domestic product (GDP).[2] It also contributes significant shares of national production in high-tech sectors and hosts an innovation ecosystem that includes Brazil's main universities and research centres. An important objective of the survey was to evaluate the technological maturity of enterprises in São Paulo, focusing on AI adoption, given that São Paulo is the most economically developed state in Brazil.

The survey was conducted by the Fundação Sistema Estadual de Análise de Dados (SEADE), the official statistics and data production organisation of the state of São Paulo, in partnership with the Regional Center for Studies on the Development of the Information Society (Cetic.br), from the Brazilian Network Information Center (NIC.br). With minor adjustments, the same survey instrument was used as that administered by the OECD/BCG/INSEAD to 840 enterprises adopting artificial intelligence (AI) across the Group of Seven (G7) countries, with the same target populations of medium and large-sized enterprises, in the same sectors of manufacturing and information and communication technology (ICT) services.

The survey results highlight that AI adoption in enterprises in São Paulo is dominated by companies procuring solutions externally. Around 70% of the data used to fuel AI applications is sourced internally. Just over half of the enterprises using AI (52%) employ some form of customised system from third parties or purchase off-the-shelf AI solutions (51%), indicating a limited level of internal development of AI applications. The most frequent AI application is in customer-facing services, reported by 49% of enterprises using AI, closely followed by process and control optimisation, cited by 44% of respondents. When considering obstacles to AI implementation, 44% of enterprises that use AI identify concerns about privacy and security as significant issues, followed closely (38%) by uncertainty about the return on investment (ROI).

The findings suggest that economic benefit could come from creating support instruments that encourage partnerships around projects for innovation in products and services using AI. Support instruments in Brazil specifically for AI are barely developed. With AI adoption in mind, benefits could be had from examining the suitability of current funding mechanisms and public programmes to support skills development and the provision of information services examined in the survey.

Following a brief section on the survey's methodology, this chapter presents the survey's main findings and a discussion on expanding the uptake of AI in Brazil, followed by a conclusion.

## Methodology

The data collection instrument was slightly adapted from the OECD/BCG/INSEAD survey questionnaire. After translating the questionnaire into Portuguese, specific wording adjustments were made to better suit the Brazilian context, incorporating insights from cognitive interviews. Overall, the adapted questionnaire is directly comparable with the survey implemented in G7 countries.

The target population comprised enterprises in the manufacturing and ICT sectors (only two ICT subsectors were considered, namely: ISIC 62: Computer programming, consultancy, and related activities; and ISIC 63: Information service activities. The manufacture of devices and components, such as semi-conductors, used in data and information processing and communication were not included under "ICT"). The survey also targeted two enterprise size classes: medium-sized (50 to 249 employees) and large-sized (more than 250 employees). Data were collected using computer-assisted telephone interviewing (CATI) and computer-assisted web interviewing (CAWI) techniques between February and July 2023.

The survey adopted a probabilistic approach, meaning that it aimed to obtain results that were statistically representative of the entire population of enterprises in the state of São Paulo. However, the sample design was not directly comparable to that adopted for the OECD/BCG/INSEAD survey in G7 countries, largely because the G7 survey is not directly generalisable to the respective population of enterprises in each country.

### *Sample design*

The registry of enterprises for the state of São Paulo was obtained from the Brazilian Secretariat of the Federal Revenue website.[3] Enterprises' main activities were identified using the International Standard Industrial Classification of All Economic Activities (ISIC) classification. After this initial selection, the registry was forwarded to the Brazilian Institute of Geography and Statistics to distinguish between medium-sized enterprises (50 to 249 employees) and large enterprises (250 or more employees). This record was divided into four cohorts, as indicated in Table 6.1. Given the need to survey only those that use AI and knowing from prior research that rates of AI use in Brazil are low, all enterprises in the four strata were approached via telephone or email (without randomised selection) to increase the number of enterprises in the sample.

**Table 6.1. The initially identified population of qualifying firms in the state of São Paulo and the response rates by cohort**

| Description | Initially identified population of qualifying firms (from the registry of enterprises) | Enterprises that responded to contacts via telephone or email (enterprises active in the state of São Paulo) | Enterprises that completed the questionnaire |
|---|---|---|---|
| Large enterprises in manufacturing | 925 | 468 | 280 |
| Large enterprises in ICT services | 71 | 22 | 10 |
| Medium-sized enterprises in manufacturing | 3 243 | 1 955 | 1 187 |
| Medium-sized enterprises in ICT services | 318 | 116 | 65 |
| Total | 4 557 | 2 561 | 1 542 |

Source: SEADE survey data.

Initially, 4 557 enterprises were approached via telephone or email. Of those, it was determined that 2 561 of these enterprises were active in the state of São Paulo. From that group, 1 542 responded to the survey questionnaire (60% of the target population). A standard correction was made for the non-responses, such that the results presented below statistically represent the 2 561 enterprises.

From the total number of enterprises considered in the survey (i.e. 2 561), only 7% were users of some type of AI application. Accordingly, despite the large number of enterprises approached, the results obtained for the full OECD/BCG/INSEAD questionnaire are limited to a final set of 167 companies. Due to the small number of completed questionnaires obtained, the margins of error (both overall and by item in the questionnaire) are high and do not allow statistical analyses that are representative of all active users by sector (ICT services and manufacturing) and by enterprise size. This implies that the results can only be provided for the total number of enterprises, and it is not possible to obtain disaggregated results by, for example, medium-sized manufacturing or large-sized manufacturing enterprises.

This probabilistic approach, applied in a context of low AI adoption, presents notable operational challenges for survey implementation. Issues include respondents' limited understanding of the concepts employed and, as the procedure described above illustrates, the need for extensive screening to find suitable respondents. As the number of enterprises utilising AI is expected to increase, survey implementation using a probabilistic approach may become more straightforward.

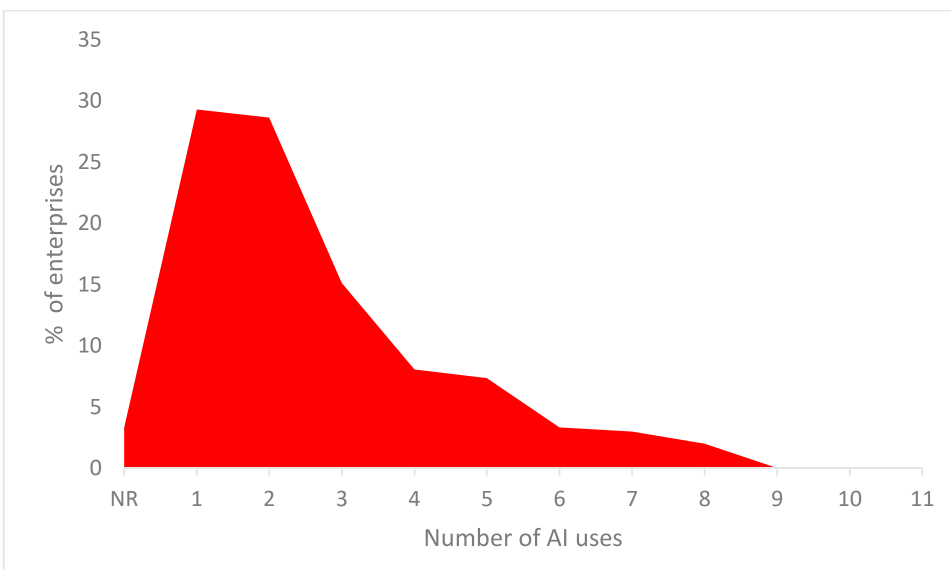
## AI use in the state of São Paulo: Main findings

### *Uses of AI, types of application, and importance of AI to enterprises*

Overall, 7% of the enterprises in the state of São Paulo use AI, a figure roughly aligned with various national-level surveys described in Chapter 2. Most of these are active users (6% of enterprises in the state). In contrast to the data obtained from G7 countries – where the sample consists of relatively advanced AI users – a vast majority of the enterprises surveyed in the state of São Paulo use only a few AI applications (58% with just one or two uses of AI compared to 4 in G7 countries) (Figure 6.1). Enterprises in the ICT services industry exhibit a higher average number of AI uses (27%) compared to manufacturers (5%). These results show that there is considerable room for expanding the use of AI in enterprises in São Paulo, transitioning from point solutions to more integrated adoption, such as incorporating customer relationship management systems.

**Figure 6.1. Distribution of uses of AI in surveyed firms in the state of São Paulo, 2023**

Share of surveyed enterprises (%) using each number of AI applications



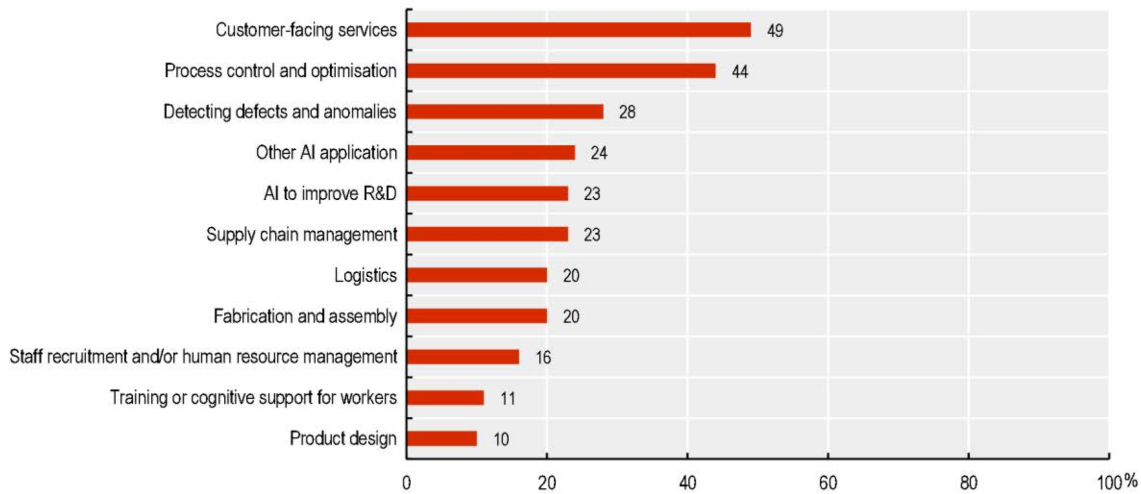

Source: SEADE survey data.

Among enterprises using AI, 49% use it in customer-facing services (Figure 6.2). The second most prevalent application of AI involves process control, automation, and optimisation of production (44%), including such uses as predictive maintenance and automated support for programmers. These results broadly align with the findings from G7 countries.

Only 23% of the surveyed enterprises use AI for research and development (R&D), considerably lower than in most G7 countries (Figure 6.2). Another 28% use AI for detecting defects and anomalies. The enterprises surveyed in G7 countries have embraced more advanced features of AI that demand greater capabilities and continuous learning. By comparison, enterprises in São Paulo are just beginning to unlock the benefits of AI, making more use of ready-made solutions, and with lower levels of internal development.

**Figure 6.2. The use of selected applications of AI in surveyed firms in the state of São Paulo, 2023**

Share of enterprises using each application of AI (%)




Note: Percentages sum to more than 100 because enterprises may use more than one application of AI.
Source: SEADE survey data.

Regarding the importance assigned to AI applications, 47% of enterprises consider AI “very important”, and 32% consider AI to be “one among a number of important considerations” (Figure 6.3). A higher share of enterprises in São Paulo considers AI of minor importance to main business processes (20%) than in G7 countries (8%). This finding reflects the presence of less advanced AI users in the Brazil sample.

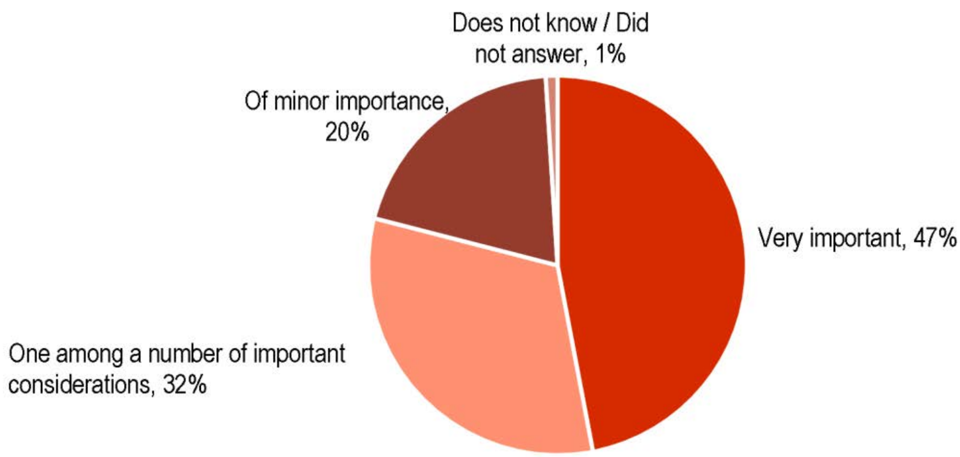
### *AI and data infrastructure*

Regarding the type of databases used, enterprises in São Paulo have prioritised their own data resources to feed AI applications. As shown in Figure 6.4, 70% of enterprises obtain necessary data from internal sources, such as data from sensors for predictive maintenance of machines. Additionally, 53% of enterprises cite customers or product/service users as the primary sources of data or data acquisition. In G7 countries, 78% of enterprises, a similar share, states that they collect data internally, but a higher share, 75%, reports using data from customers and users.

Partnerships with external organisations that function as a data source, among other things, are significant but not as common as in the enterprises surveyed in G7 countries. Such partnerships include those with private enterprises (25%), research institutes (24%), government organisations (21%) and private data providers (20%). Overall, the results reflect that the use of internal and other proprietary data are more widespread in Brazil. In general, the use of external data (in addition to the use of internal data), which is more frequent in the G7 countries, is associated with greater data maturity.

**Figure 6.3. The importance of AI to enterprises' main business processes, among firms surveyed in the state of São Paulo, 2023**

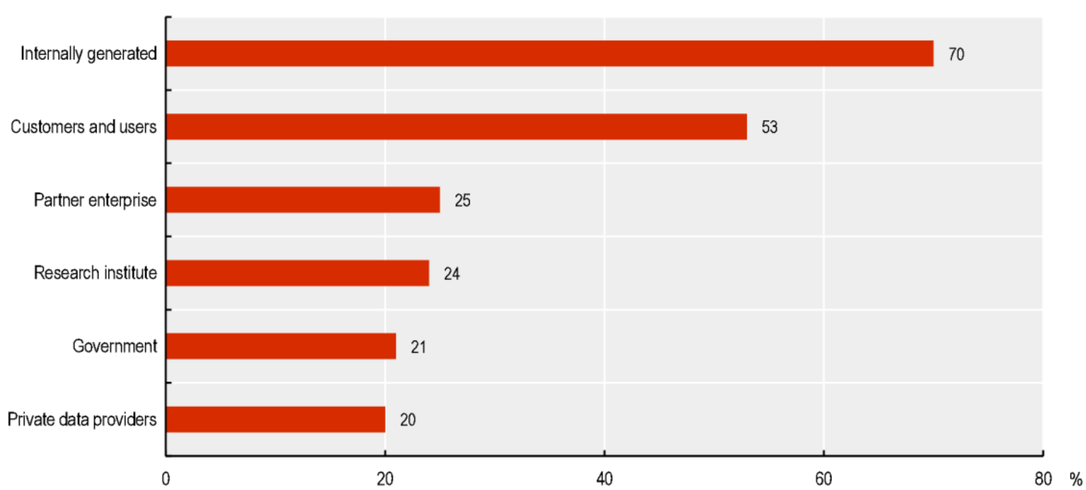
Share of enterprises per attributed level of importance of AI (%)




Source: SEADE survey data.

**Figure 6.4. The sources of enterprises' data for AI, among firms surveyed in the state of São Paulo, 2023**

Share of enterprises using selected sources of data for AI (%)

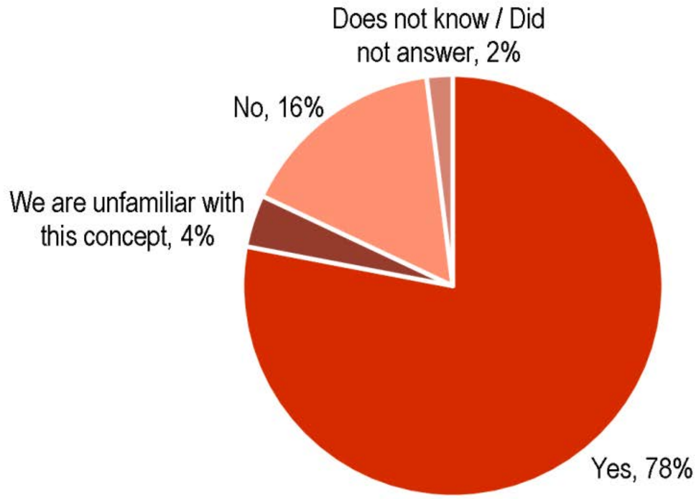



Source: SEADE survey data.

From the overall sample of enterprises that use some type of AI, 78% adopt data management solutions like remote servers, data lakes or data warehouses (Figure 6.5). This result also aligns with findings obtained among G7 countries, indicating that most enterprises are cognisant of the prerequisites for AI deployment.

**Figure 6.5.** **Use of or familiarity with data management solutions among firms surveyed in the state of São Paulo, 2023**

Share of enterprises in each category of use or familiarity (%)




Source: SEADE survey data.

### *Practices and partnerships to adopt and develop AI*

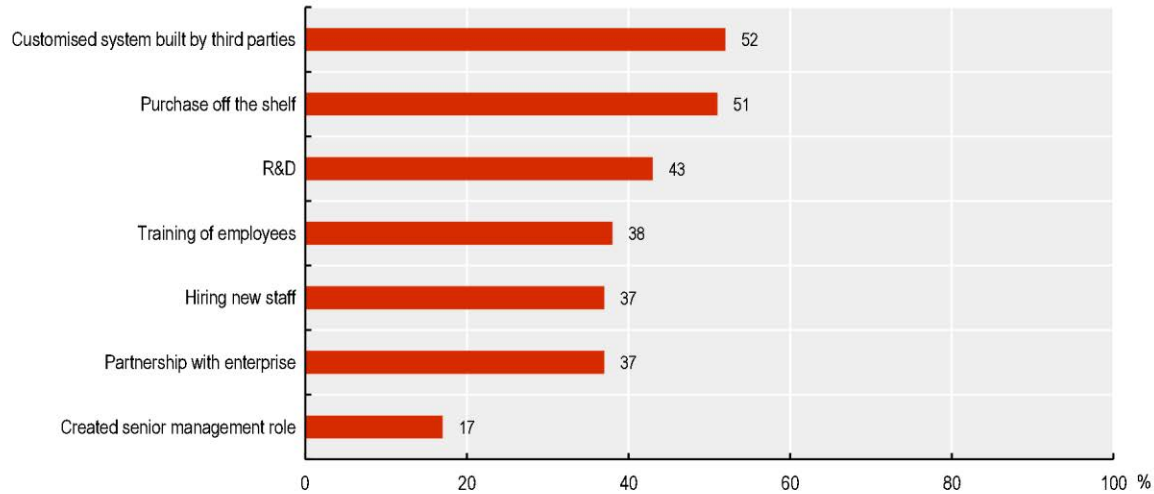
Approximately 52% of AI-using enterprises in the state of São Paulo turn to third-party customised systems, while 51% adopt AI by acquiring new software or hardware or hiring consultancy services. Additionally, 43% invest in their own R&D to develop AI (Figure 6.6). In G7 countries, a higher proportion of enterprises (70%) were found to engage in R&D in AI for their own use, followed by the development of customised systems and procurement of off-the-shelf software or hardware.

About 37% of enterprises that use AI cite collaboration with other enterprises that have capabilities in the field as a means of adopting or developing AI. This is low compared to G7 countries, where this figure is around or above 40% in all but one country, and, in some cases, above 50%. Employee training to help develop or apply AI was cited by 38% of enterprises, while in the G7 countries, this was mentioned by 75% of enterprises.

Only 17% of AI-using enterprises have established a senior management position or formed a dedicated team for AI. The limited existence of leadership positions in AI focused on team direction and decision making is discussed below in the section on human resources. The figures for São Paulo indicate a relatively low degree of emphasis on establishing leadership positions to develop AI. In contrast, the G7 survey revealed that around half of enterprises had created senior management roles or dedicated teams with responsibilities for AI.

**Figure 6.6. Practices to adopt and develop AI among firms surveyed in the state of São Paulo, 2023**

Share of enterprises using each method to adopt or develop AI (%)

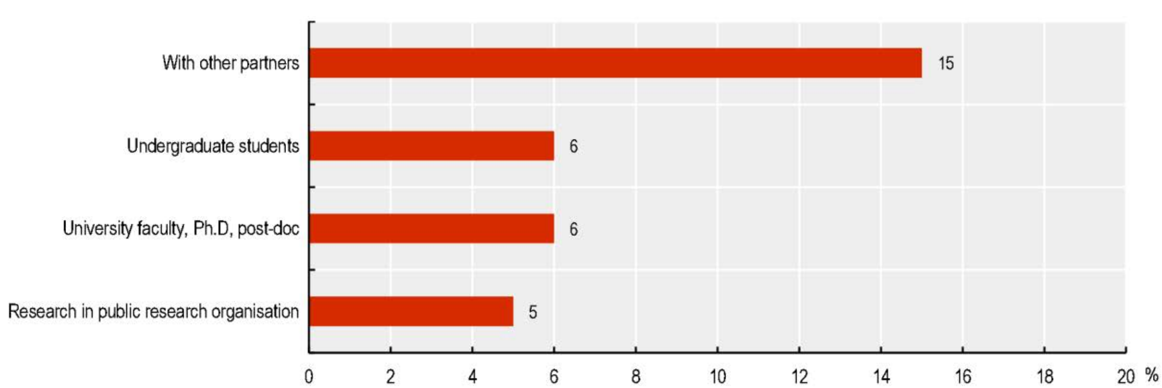



Note: Percentages sum to over 100 because enterprises may use multiple methods.
Source: SEADE survey data.

Figure 6.7 shows the incidence of partnerships between enterprises and other institutions to develop AI applications. Evident is the limited extent of partnerships with researchers. Undergraduate students, faculty, doctoral students and postdoctoral researchers are mentioned as collaborators in only 6% of cases, while partnerships with researchers outside of universities occur in only 5% of AI-using enterprises. Despite the evident importance of AI as an emerging technology, there is a significant gap in building collaborative partnerships. For instance, among G7 countries, over half of the surveyed enterprises have collaborated with university faculty, PhD or postdoctoral students. This indicates a more mature environment for fostering academic and business relationships, potentially catalysing innovation and company creation. Figure 6.7 also shows that the most frequent form of partnership occurs with partners not linked to academic or research organisations.

**Figure 6.7. Partnerships to adopt or develop AI among firms surveyed in the state of São Paulo, 2023**

Share of enterprises engaged in each partnership type (%)




Source: SEADE survey data.

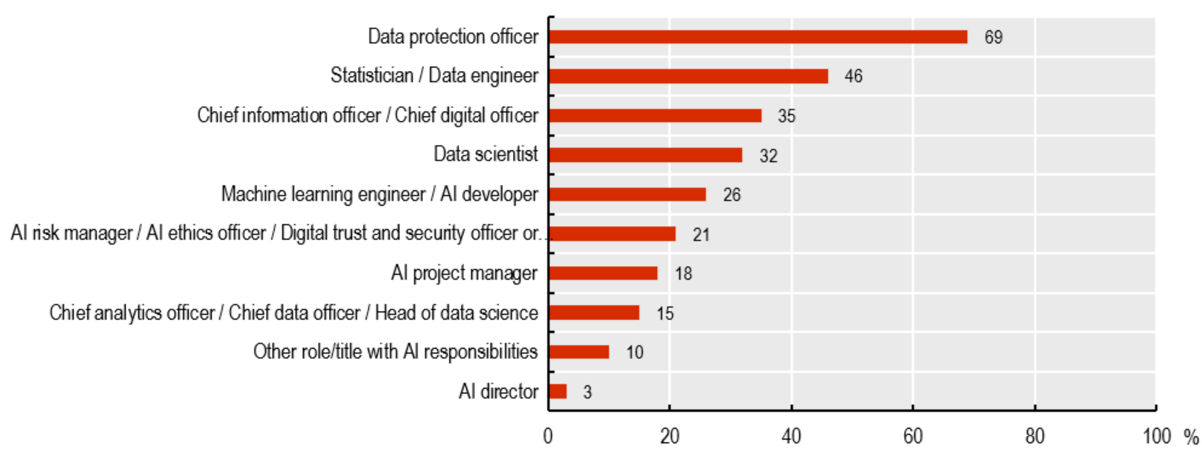
### *Human resources for AI*

The level of awareness of the disruptive consequences of adopting AI can also be assessed using data on the organisational structure of enterprises. Brazil's 2021 ICT Enterprises Survey showed that 13% of Brazilian companies use some type of AI. However, 39% of large companies do so. This significantly higher rate of adoption stems from large companies' substantial investments in software and hardware, coupled with the greater availability of financial and human resources dedicated to experimentation with disruptive technologies (Brazilian Internet Steering Committee, 2022[1]).

Figure 6.8 presents data on the existence of positions related to AI in enterprises in the state of São Paulo. The most prevalent position relating to data management, processing and AI is that of data protection officer (DPO), which is present in 69% of enterprises. This role typically entails responsibility for defining policies, standards and practices to ensure data quality, security and compliance. The widespread presence of DPOs indicates a concern among enterprises in the state of São Paulo with data security.[4] This situation may be associated with the Brazilian General Data Protection Law, enforced since 2020. In response to that legislation, enterprises have begun to emphasise internal data governance, instituting more robust processes for handling personal data.[5]

**Figure 6.8. The prevalence of professional roles relevant to AI among firms surveyed in the state of São Paulo, 2023**

Share of enterprises with the associated role (%)




Note: Percentages sum to over 100 because enterprises may have more than one of the cited roles.
Source: SEADE survey data.

Managerial positions related to AI are still rare among enterprises in the state of São Paulo, even those that use AI. Only 21% of enterprises that apply some form of AI indicate the existence of a role like an AI risk manager or a position responsible for AI ethics, for trust and digital security, or an equivalent function (Figure 6.8). Only 18% of enterprises have AI project manager roles.

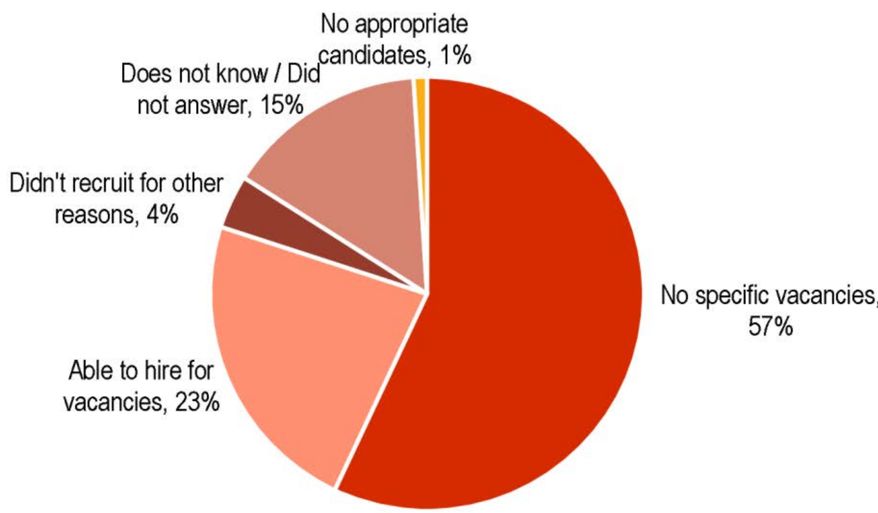
Regarding C-suite positions, 35% of enterprises using some form of AI have chief information officer and/or chief digital officer positions. In other words, just over one-third of enterprises that use AI have established leadership positions formally responsible for an effective information technology (IT) infrastructure or digital initiatives oriented to innovation. This finding indicates a relatively restricted use of AI.

As for the presence of senior staff responsible for using data for new strategic initiatives and business objectives, only 15% of enterprises have a chief analytics officer, chief data officer, and/or head of data science positions. This underscores the overall finding of a limited presence of professionals dedicated exclusively to data governance, an essential activity for developing AI applications.

In terms of the workforce, and relative to G7 countries, a pattern exists of lower demand for AI-related talent. Notably, 57% of enterprises in São Paulo report not opening specific positions for AI (Figure 6.9), while this proportion was only 20% among G7 countries. Furthermore, only 23% of enterprises in the state of São Paulo indicate hiring professionals for AI roles, compared to 67% among G7 countries. The somewhat incipient level of AI adoption among enterprises in the state of São Paulo suggests that there might not be significant problems with talent availability at present. However, this may not persist, particularly as more AI solutions enter the market.

**Figure 6.9. Recruitment of staff with training in AI, machine learning, or related areas among firms surveyed in the state of São Paulo, 2023**

Share of enterprises in each category (%)




Source: SEADE survey data.

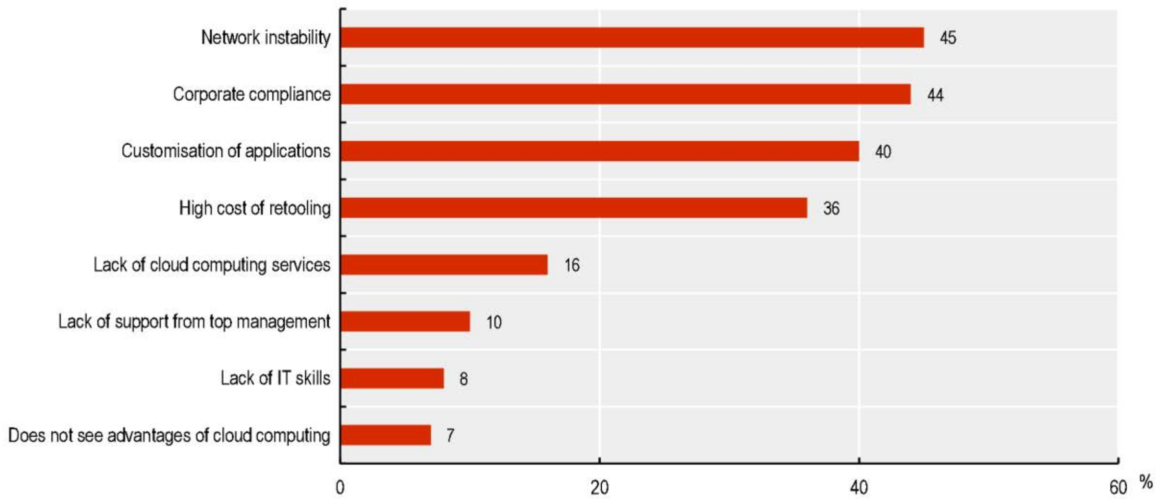
### *Obstacles to adopting AI*

Cloud computing provides critical infrastructure and cloud-based services to support AI applications and to make their development and deployment more accessible and scalable. The integration of these two technologies – infrastructure and services – is driving many advances in the field of AI and is present in a wide variety of industries. Among enterprises in the state of São Paulo, 70% indicate that they use cloud computing without difficulty. Only 7% of enterprises say they do not see any advantages in using cloud computing (Figure 6.10).

The cost of retooling systems was the most frequently indicated obstacle to cloud use among enterprises in G7 countries (cited by 60% of enterprises in manufacturing and 56% in ICT).

**Figure 6.10. Obstacles to the use of cloud computing among firms surveyed in the state of São Paulo, 2023**

Share of enterprises experiencing each obstacle (%)




Note: Percentages sum to over 100 because enterprises may experience more than one obstacle.
Source: SEADE survey data.

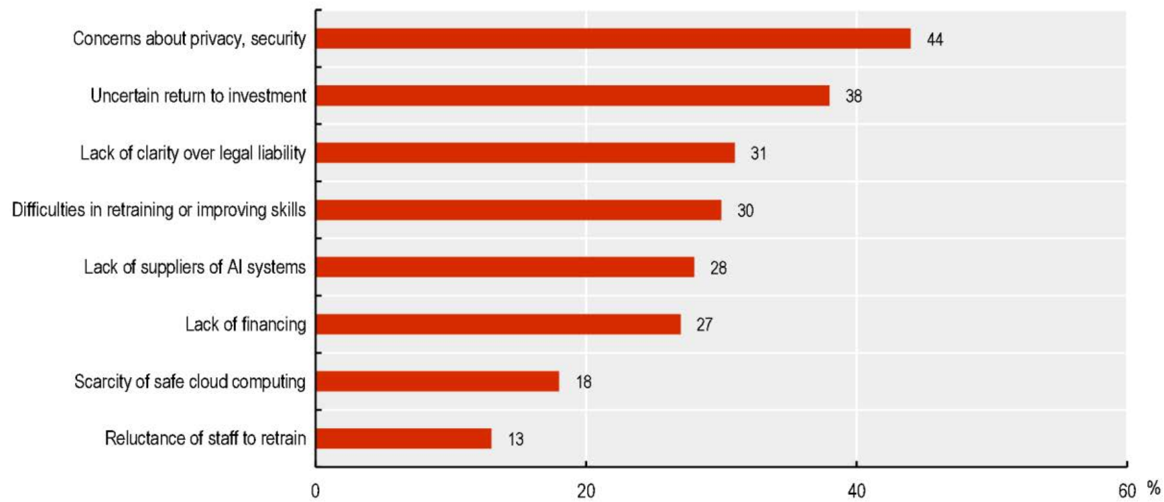
This problem affects 36% of enterprises in the state of São Paulo. Regarding connectivity, 45% of enterprises in São Paulo cited concerns about network stability as a significant limiting factor in adopting cloud computing, a concern shared by a comparable fraction of enterprises in G7 countries.

For 44% of enterprises, the biggest obstacle to using AI relates to privacy, data protection or security (Figure 6.11). These results are connected to earlier observations that in enterprises based in São Paulo, there is a notable convergence between concerns about personal data protection and the utilisation of AI. Indeed, because much use of AI in enterprises in the state of São Paulo draws on internal data, it can be inferred that customer data are being utilised. This raises several questions regarding proper compliance with the law.

The difficulty in estimating the ROI in AI applications – a concern also described in Chapters 3 and 5 – was highlighted by 38% of respondents. In G7 countries, concerns regarding uncertain rates of ROI in AI were cited by 62% of enterprises in manufacturing and 56% in the ICT services industry.

**Figure 6.11. Obstacles limiting the implementation of AI among firms surveyed in the state of São Paulo, 2023**

Share of enterprises limited in using AI by each category (%)




Note: Percentages sum to over 100 because enterprises may experience more than one obstacle.
Source: SEADE survey data.

## Expanding the uptake of AI in Brazil and the role of the public sector

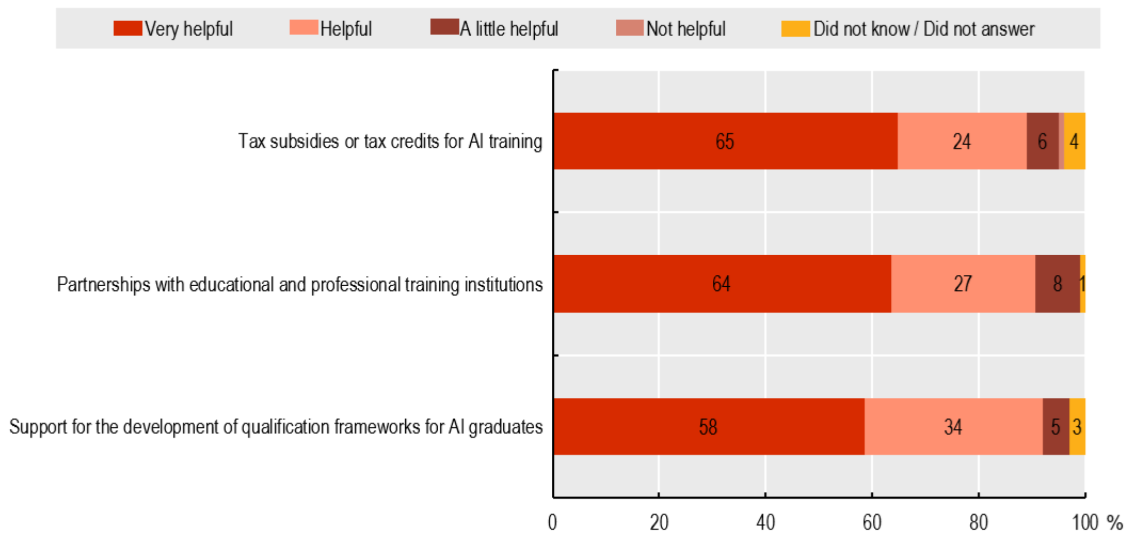
While Brazil's public authorities have implemented many initiatives to support business innovation, none have been specifically tailored to AI to date. Enterprises were asked about the usefulness of three possible support mechanisms. Specifically, enterprises were queried on how helpful the following types of support could be to increase AI skills among staff:

- partnerships with educational and vocational institutions
- tax allowances or tax credits for training in AI
- support to develop qualification frameworks for graduates in the field of AI.

As is the case in G7 countries, most enterprises indicate that one or another form of public support would help strengthen staff skills in AI. Figure 6.12 shows that 65% of enterprises that use some form of AI consider tax subsidies or tax credits for AI-related training as "very useful". Some 64% also consider help to establish partnerships with educational and professional training institutions "very useful". An only slightly lower incidence of support was shown for the development of qualification frameworks for graduates in the AI field, with 58% considering that this would be "very useful" and 34% deeming it "useful".

### Figure 6.12. Perceived usefulness of selected support measures to strengthen staff skills in AI among firms surveyed in the state of São Paulo, 2023

Share of enterprises expressing agreement (%)




Source: SEADE survey data.

Enterprises were asked about how useful different types of mostly information services provided by the public sector could be to their use and development of AI:

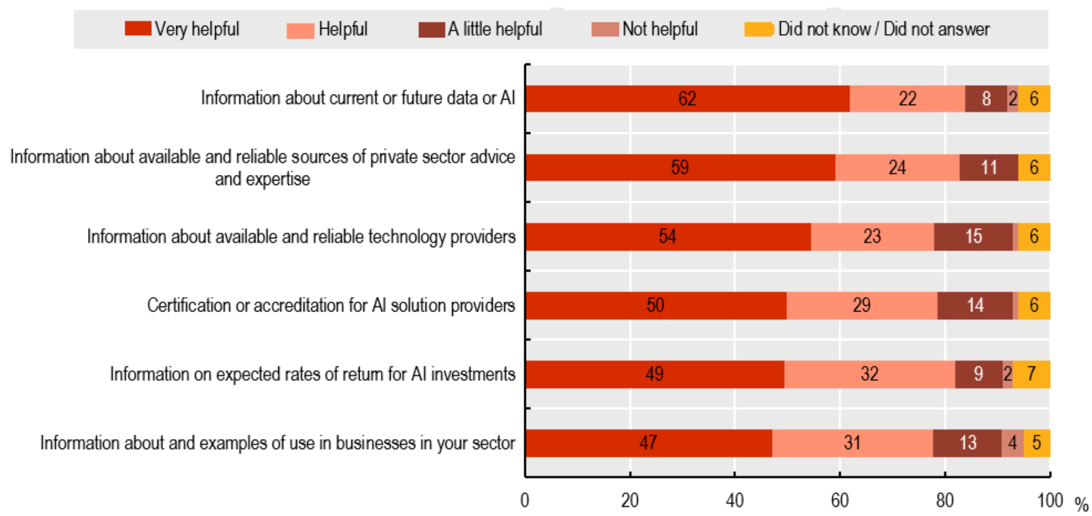
- information on and examples of business use cases in the firm's industry
- information on expected rates of ROI in AI
- information on available and reliable technology vendors
- information on available and reliable sources of private-sector advice and expertise
- certification or accreditation schemes for AI solution providers
- information on current or forthcoming regulations around data or AI.

As in G7 countries, a large majority stated that information services provided by the public sector would be "helpful" or even "very helpful" to their use of AI. For any of the services considered, no less than 78% of enterprises indicate that they would be at least "helpful".

Figure 6.13 shows that 62% of the respondent enterprises consider that information on current or forthcoming regulations about data or AI would be "very useful". Another 59% held that the dissemination of information about available and reliable sources of private-sector advice and expertise would be "very useful". Some 54% also held that information about available and reliable technology providers would be "very useful".

**Figure 6.13. Perceived usefulness of different information services for AI adoption and development among firms surveyed in the state of São Paulo, 2023**

Share of enterprises expressing agreement (%)




Source: SEADE survey data.

With high levels of utility accorded to all of the selected public services, it is reasonable to argue that the role of the public sector in promoting new technologies in AI is important and should cover both the development of appropriate regulations and the provision of information to help equip managers to make better decisions in implementing AI.

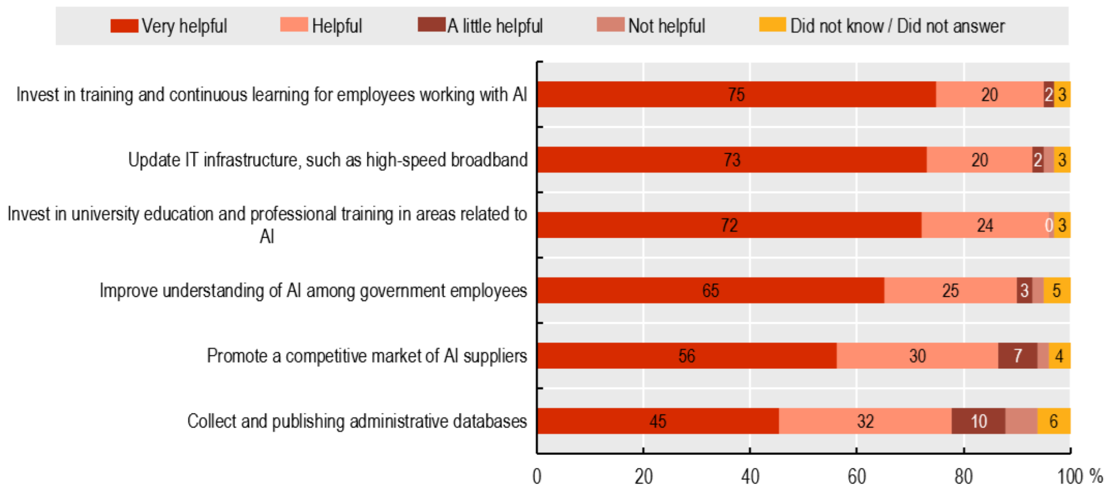
Finally, regarding broader public sector initiatives to support the adoption of AI, investment in university education and professional training in AI is particularly important. Fully 75% of the enterprises that use some type of AI declare such initiatives “very useful” (Figure 6.14).

It is widely known that IT infrastructure and connectivity problems in some regions of Brazil require public sector incentives to be fully resolved.[6] It is perhaps unsurprising then that 73% of enterprises cite upgrading IT infrastructure, such as high-speed broadband, as “very useful” for the adoption of AI.

Some 45% of enterprises maintain that collecting and publishing administrative databases would also be “very useful”. Despite the fundamental role data plays as an input for AI applications and the public sector’s efforts to make data available, this relatively low score indicates a pattern of intensive use of private data sources.

**Figure 6.14. Perceived usefulness of types of support for AI adoption and development among firms surveyed in the state of São Paulo, 2023**

Share of enterprises expressing agreement (%)




Source: SEADE survey data.

## Conclusion

The survey results indicate that the use of AI among large and medium-sized enterprises in the manufacturing and ICT services sectors in the state of São Paulo is still at an early stage of maturity. The data corroborates the findings of previous research in Brazil, such as the Brazilian Network Information Center, Regional Center for Studies on the Development of the Information Society and Brazilian Internet Steering Committee (2022[1]), which highlighted a low presence of AI across enterprises of all sizes and in all sectors of economic activity. The data also indicates that AI is mainly present in the processes most susceptible to automation. A particularly concerning point in comparison with G7 countries is the limited role of R&D in adopting AI.

Many opportunities exist for enterprises to promote the internal development of AI and to expand relationships with external partners. Beyond the enterprises themselves, the findings suggest that economic benefit could come from creating support instruments that encourage partnerships around projects for innovation in products and services using AI. Assessment of the suitability of current funding mechanisms and public programmes to support skills development and the provision of the information services examined in the survey would be worth pursuing.

There are some points to highlight that could contribute to improving the utility of the survey questionnaire. These concern adjustments to the questionnaire itself and changes to the data collection process. Regarding the questionnaire, one measure could be to expand the scope of research to enterprises that do not currently use AI but intend to do so or are in the initial steps of implementing AI for the first time. This would help to better understand the difficulties experienced in using AI and how these difficulties manifest in the different phases of implementation, such as in decision making around investments, the organisation and management of data, equipment acquisition and staff hiring. Such a shift to a broader set of themes on AI uptake would be particularly important in contexts where the overall use of AI in the corporate sector is low, which is the present reality in Brazil. In the current questionnaire, enterprises that do not use AI actively did not complete the survey.

Regarding data collection, in a future iteration of the survey, it could be helpful to identify specifically qualified persons in the responding enterprises to answer the questionnaire in advance. This is because the survey encompasses varied and specific topics (e.g. implementation obstacles, insights into the most helpful support services for the enterprise, and partnership arrangements). An alternative would be to consider having more than one respondent, as the topics addressed may be the responsibility of more than one team within the enterprise.

## References

Brazilian Internet Steering Committee (2022), *Survey on the Use of Information and Communication Technologies in Brazilian Enterprises*, https://cetic.br/media/docs/publicacoes/2/20221121122540/tic_empresas_2021_livro_eletronico.pdf. [1]

## Notes

[1] For more information on the last census, see https://censo2022.seade.gov.br/.

[2] Additional information on the GDP of São Paulo is available at https://pib.seade.gov.br/mensal/.

[3] Every company in Brazil has a unique registration number. These are publicly available and provide basic information, such as the company's address, whether it is active or not, and its size. This information can be accessed at https://solucoes.receita.fazenda.gov.br/servicos/cnpjreva/cnpjreva_solicitacao.asp.

[4] According to the Brazilian Network Information Center, Regional Center for Studies on the Development of the Information Society and the Brazilian Internet Steering Committee (2022[1]), only 17% of Brazilian enterprises had appointed DPOs (41% of large enterprises, 29% of medium enterprises, and 15% of small enterprises). Although the Brazilian General Data Protection Law refers to the DPO as a person, there are no restrictions on the creation of interdepartmental data protection teams, or even hiring third-party agents.

[5] During cognitive testing of the survey instrument, when asked about aspects of AI regulation, many respondents replied based on the procedures their enterprises were following to comply with the Brazilian General Data Protection Law. As of this writing, Brazil did not have specific regulations for AI.

[6] Cetic.br conducted case studies on the deployment of the Industrial Internet of Things in manufacturing enterprises, revealing that challenges related to network stability and availability were identified as significant obstacles to increased sensor utilisation in companies' machines.

# Annex A. Comparisons among recent AI surveys

## Table A.1. Selected features of recent national and supranational surveys of AI in firms

| Survey<br><br>(A) | Technologies, functionalities, activities<br>(B) | Sectors and sample size<br><br>(C) | Questions similar to those in the OECD/BCG/INSEAD survey |
|---|---|---|---|
| **Canada**<br>"2017 Survey of Innovation and Business Strategy" | Internet of Things<br>AI<br>Geomatics or geospatial technologies<br>Nanotechnology<br>Biotechnology<br>Blockchain | Multiple sectors, including utilities, manufacturing, mining, oil and gas.<br><br>13 252 firms, each with at least 20 employees and revenues of CAN 250 000 or more | Questions on **obstacles to innovation** which are of indirect relevance to AI diffusion barriers:<br><br>• uncertainty and risk<br>• skills<br>• regulatory or government competition policy<br>• internal funding<br>• external financing |
| **Germany**<br>"Survey on the Use of Artificial Intelligence, 2020" | Speech recognition<br>Image or object recognition<br>Pattern recognition<br>Algorithmic decision making<br>Automation of machines or vehicles | Unknown at the time of writing | **Sourcing strategies**<br>Are the AI applications in your company based on software developed in-house, on open-source software, commercial software packages, or individual solutions for your company from external software providers?<br><br>**Barriers to adoption**<br>Please tell me in each case whether this aspect is a major problem, a minor problem or not a problem for your company when using AI:<br>• difficulty finding appropriate use cases for AI<br>• proof of the added value of AI over alternative methods<br>• lack of employee skills in AI methods<br>• integration of AI in existing systems, such as IT systems or machines, etc. |
| **Germany**<br>"Artificial Intelligence and Industrial Innovation: Evidence From Firm-Level Data (ZEW)" | Language/text understanding<br>Image/pattern recognition<br>Machine learning<br>Knowledge/expert systems | Mining<br>Manufacturing<br>Utilities<br>Service sectors (wholesale, transportation, information and communication, banks and insurance, professional and technical services, business support services). | **Sourcing strategies, i.e.:**<br>• mainly developed in-house<br>• mainly developed by others<br>• both in-house and by others<br><br>No related question on adoption barriers |

| Survey<br><br>(A) | Technologies, functionalities, activities<br>(B) | Sectors and sample size<br><br>(C) | Questions similar to those in the OECD/BCG/INSEAD survey |
|---|---|---|---|
| | | Responses from<br>8 821 firms | |
| **Sweden**<br>“Artificial intelligence in Sweden (Statistics Sweden, 2020[1])” | Do firms use AI to:<br><br>- develop or increase knowledge of customers or users<br>-develop a new product or service<br>-improve an existing product or service<br>-develop or improve internal processes<br>-other usage | Manufacturing<br>Energy and recycling<br>Construction<br>Wholesale and retail trade; repair of motor vehicles and motorcycles<br>Transportation and storage<br><br>Sample size: 3 831 firms | **Obstacles to the use of AI, i.e.:**<br>• knowledge of existing technologies and applications<br>• employees´ skills, training or experience<br>• compatibility with existing software or hardware<br>• data (e.g. quality issues, lack of data)<br>• services or equipment costs<br>• data security or data integrity |
| **United Kingdom**<br>“Understanding the UK AI Labour Market: 2020” | Robotics – training robots to interact with the world in generalisable and predictable ways<br><br>Computer vision – gaining high-level understanding from digital images or video<br><br>Natural language processing<br><br>Collaborative systems – autonomous systems that can work collaboratively with other systems and with humans<br><br>Bio-inspired computing models – this includes evolutionary algorithms and algorithmic game theory<br><br>Bio-inspired hardware – new forms of AI-enhanced hardware, e.g. using neuromorphic computing techniques<br><br>Edge intelligence – combining AI with edge computing, as in the Internet of Things and “smart home” devices<br><br>Classification – assigning a class or label to a previously unseen input, e.g. to identify spam emails<br><br>Predictive machine learning – estimating the value of a discrete variable based on historical data<br><br>Regression for machine learning – estimating the value | 118 AI firms, including firms whose core business was developing AI-led products or services and others in wider sectors developing or using AI tools, technologies or techniques to improve their products, services or internal processes. | **What AI is used for:**<br>• to predict<br>• to automate<br><br>**Policy priorities and support relevant to data:**<br>• providing funding (e.g. loans, grants, tax benefits)<br>• the data-related regulatory framework<br>• access to data science talent |

| Survey<br><br>(A) | Technologies, functionalities, activities<br>(B) | Sectors and sample size<br><br>(C) | Questions similar to those in the OECD/BCG/INSEAD survey |
|---|---|---|---|
| | of a continuous variable based on historical data | | |
| **United States**<br>"Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey 2020 (US Census Bureau)" | Augmented reality<br>Machine learning<br>Machine vision<br>Natural language processing<br>Cloud computing<br>Robotics<br>Radiofrequency identification (RFID)<br>Automated vehicles | All private, non-farm sectors, including agriculture, manufacturing, finance and healthcare<br><br>583 000 firms<br>(i.e. responses) | **Technologies used (see Column B)**<br><br>No related questions on AI sourcing strategies or adoption barriers |
| **United States**<br>"Survey of Manufacturers, 2019, Information Technology and Innovation Foundation" | AI<br>Digital modelling/prototyping (CAD, CAE, CAM)<br>Cloud computing<br>Industrial robotics<br>Computer numerical control (CNC) machining<br>3-D printing<br>Internet of Things<br>Big data analytics<br>Augmented reality/Virtual reality (AR/VR)<br>Digital twins | Manufacturing<br><br>60 responses (enterprises with annual turnover between USD 500 million and USD 10 billion) | No related questions on sourcing strategies or adoption barriers |
| **European Union**<br>"European Enterprise Survey on the Use of Technologies based on Artificial Intelligence 2020" | Natural language processing<br>Anomaly detection<br>Computer vision<br>Sentiment analysis<br>Machine learning<br>Recommendation and personalisation engines<br>Process optimisation<br>Process automation<br>Autonomous machines<br>Creative and experimentation activities | Wide variety of NACE sectors: from Sector A (Agriculture, Hunting and Forestry) to Sector Q (Extraterritorial Organisations and Bodies)<br><br>Aims to achieve responses from<br>9 640 firms from across the EU27 | **A number of the processes listed in Column B** (particularly process optimisation, process automation and autonomous machines)<br><br>**AI sourcing strategies**<br><br>**Various obstacles to adoption, i.e.:**<br><br>External obstacles:<br>• public or external funding<br>• liability for damage caused by AI<br>• the need for new laws or regulations<br>• access to high-quality private data<br>• access to or availability of public data<br><br>Internal obstacles:<br>• hiring staff with the right skills<br>• the cost of adoption<br>• the cost of adapting operational processes<br>• skills of existing staff<br>• understanding of algorithms<br>• IT infrastructure<br>• internal data |
| **European Union**<br>"Eurostat, Community Survey on ICT Usage | AI<br>Text mining<br>Machine learning | NACE Rev. 2 Sections C to N, excluding Section K, but including | **Sourcing strategies, i.e.:**<br>• developed by own employees |

| Survey<br>(A) | Technologies, functionalities, activities<br>(B) | Sectors and sample size<br>(C) | Questions similar to those in the OECD/BCG/INSEAD survey |
|---|---|---|---|
| and E-commerce in Enterprises 2021” | Computer vision<br>Speech recognition<br>Natural language processing<br>Deep learning<br>Robotic process automation<br>Autonomous robots<br>Self-driving vehicles<br>Autonomous drones | manufacturing<br><br>The survey population consists of enterprises with ten or more employees. Out of around 1.5 million EU enterprises with at least ten persons employed, a sample of almost 142 000 were surveyed (survey 2020). Of the 1.5 million enterprises, approximately 83% were small enterprises (10-49 persons employed), 14% medium (50-249) and 3% large (250 or more). | • commercial software or systems modified by own employees<br>• open-source software or systems modified by own employees<br>• ready-to-use commercial software or systems<br>• external providers contracted to develop or modify<br><br>**Barriers to adoption, i.e.:**<br>• cost<br>• expertise in the enterprise<br>• incompatibility with existing equipment, software or systems<br>• difficulties with availability or quality of necessary data<br>• concerns regarding data protection and privacy<br>• lack of clarity about legal consequences (e.g. liability in case of damage caused by the use of AI)<br>• useful or not for the enterprise |
| **European Union + European Investment Bank**<br>“Artificial Intelligence, Blockchain and the Future of Europe: How Disruptive Technologies Create Opportunities for a Green and Digital Economy 2021” | AI<br>Blockchain | 100 SMEs located in the 27 member states using AI and blockchain | This study aimed to identify and address general market failures and access-to-finance barriers faced by SMEs (although survey questions are not included in the overall report). |

Source: OECD desk research.

## References

Statistics Sweden (2020), *Artificiell intelligens i Sverige (Artificial intelligence in Sweden)*, Statistics Sweden, https://www.scb.se/contentassets/4d9059ef459e407ba1aa71683fcbd807/nv0116_2019a01_br_xftbr2001.pdf. [1]

# Annex B. Mapping ISIC and national industry classification systems

### Table B.1. Mapping of target ISIC Rev. 4 codes against national industry classification systems

| | | ISIC Rev 4. | | |
|---|---|---|---|---|
| | | Manufacturing | ICT subsectors | |
| | National Industry Classification System | Section C. Manufacturing | 62. Computer programming, consultancy, and related activities | 63. Information services activities |
| Brazil | CNAE 2.2 | Section C | 62 | 63 |
| Canada | NAICS 2017 | 31-33 | 54151 | 518210<br>519130<br>519110<br>519190 |
| France | NAF Rev.2 | Section C | 62 | 63 |
| Germany | WZ 2008 | Section C | 62 | 63 |
| Italy | ATECO 2007 | Section C | 62 | 63 |
| Japan | JSIC Rev.13 | Section E | 3911<br>3912 | 3921<br>3922<br>3929<br>4011<br>4012<br>4013<br>4161 |
| United Kingdom | UK SIC 2007 | Section C | 62 | 63 |
| United States | NAICS 2017 | 31-33 | 54151 | 518210<br>519130<br>519110<br>519190 |

Note: ISIC stands for International Standard Industrial Classification of All Economic Activities; CNAE is the national version of NACE (Nomenclature of Economic Activities in the European Community); NAICS stands for North American Industry Classification System; NAF stands for *nomenclature d'activités française*; WZ is the German Classification of Economic Activities; ATECO is the Italian Classification of Economic Activity; JSIC stands for Japan Standard Industrial Classification; UK SIC stands for UK Standard Industrial Classification of Economic Activities.
Source: OECD desk research.

# Annex C. The OECD/BCG/INSEAD survey questionnaire

The text below shows the screening and other questions in the OECD/BCG/INSEAD survey questionnaire. Respondents were first presented with a definition of AI, shown in Annex Box 1.C.1.

### Box C.1. What is "artificial intelligence"?

Artificial intelligence (AI) is a system that displays intelligent behaviour by analysing an environment and taking actions, with some degree of autonomy, to achieve specific goals. These systems collect and process data using statistical machine learning to predict, recommend or decide the best action to achieve specific goals. AI-based systems can be purely software or embedded in hardware.

Applications for AI can include (but are not limited to):

- image and video analysis for diagnostics or facial recognition systems based on computer vision or voice recognition systems,
- machine translation, speech-to-text programs, text analytics or chat robots based on natural language processing,
- decision support, forecasting systems, security systems, traffic analysis, fraud detection, recommendation systems, process optimisation or recruitment software based on machine learning,

autonomous drones, self-improving robots for production or warehouse tasks or self-driving vehicles.

## Screening questions

| How many employees does your enterprise have in total? |
|---|
| • Between 10 and 50 |
| • Between 51 and 249 |
| • Between 250 and 499 |
| • Between 500 and 2 500 |

| What is the enterprise's major industry? |
|---|
| • Manufacturing machinery |
| • Chemicals |
| • Pharmaceuticals |
| • Automotive: Vehicles, transport equipment and components |
| • Mechanical components |

| | |
|---|---|
| • | Electrical equipment (including domestic appliances) |
| • | Computers, electronics and optical products and parts |
| • | Other manufacturing industry – please state |
| • | Enterprises engaged in writing, modifying, testing and supporting software |
| • | Planning and designing computer systems that integrate computer hardware |
| • | Software and communication technologies |
| • | Managing and operating clients' computer systems and/or data processing facilities |
| • | Operating or supporting the activities of web search portals |
| • | Data processing and hosting activities, and online platforms |
| • | None of the above |

| Does your enterprise use artificial intelligence actively or passively? | |
|---|---|
| • | No, we do not use artificial intelligence at all |
| • | Yes, we use it passively |
| • | Yes, we use it actively |

| Does your enterprise use artificial intelligence applications in any of the following ways – either in-house or through contracts with an external service supplier? | | |
|---|---|---|
| | Yes | No |
| Product design, for instance, to generate new designs autonomously or with limited human supervision | | |
| Fabrication and assembly, for instance, using robots and other machine systems that have a high degree of autonomy | | |
| Process control and optimisation, for instance, to automatically optimise production processes, perform predictive maintenance, or automatically assist programmers | | |
| Detecting defects and anomalies, for instance, to automate visual inspection of products, or to help software developers test and identify defects in code | | |
| Supply chain management, for instance, for demand forecasting and scheduling optimisation | | |
| Logistics, for instance, for warehouse automation or delivery optimisation | | |
| Training or cognitive support for workers, such as systems for enhancing workforce training (using virtual reality) or to support the workforce using augmented reality | | |
| Staff recruitment and/or human resource management, such as systems that help to select potential recruits based on analysis of past performance of workers with comparable qualifications | | |
| AI to improve research and development, such as machine learning systems to accelerate materials and drug discovery, or experiment with new programming solutions. Such services are often provided by private R&D laboratories. | | |
| Customer-facing services, for instance, in pricing decisions, to improve the safety of products that are part of the Internet of Things (IoT), process data from social media to help predict customer behaviour, or to automatically provide users with problem solutions on service desks | | |

| Please indicate your job title: | |
|---|---|
| • | IT Manager |
| • | Head of Data Science |
| • | AI Project Manager |
| • | Chief Information Officer |
| • | Chief AI Officer |
| • | Chief Analytics Officer |
| • | Chief Data Officer |
| • | Chief Executive Officer |
| • | Other – please specify |

| In which country is your enterprise located? |
| --- |
| • Canada |
| • France |
| • Germany |
| • Italy |
| • Japan |
| • United Kingdom |
| • United States |
| • None of the above |

## Survey questions for enterprises passing the screening section

### Question 1.

| How important are AI applications to your enterprise's core business processes? |
| --- |
| • Critically important |
| • One among a number of important considerations |
| • Of minor importance |

### Question 2.

| In approximately which year was your enterprise incorporated? |
| --- |
| • 1950 or earlier |
| • 1950-1960 |
| • 1960-1970 |
| • 1970-1980 |
| • 1980-1990 |
| • 1990-2000 |
| • 2000-2010 |
| • 2010-2020 |
| • After 2020 |

### Question 3.

In the past 12 months, has your enterprise collected or otherwise acquired data from any of the following sources?

| | Yes | No |
| --- | --- | --- |
| Data collected internally from processes and staff | | |
| Data collected from customers or suppliers | | |
| Data from private data providers, such as organisations dedicated to producing and selling data | | |
| Data from a partner enterprise | | |
| Data from a research institute | | |
| Data from the public sector | | |

### Question 4.

| Does your enterprise use a data management solution, such as a data lake? |
| --- |
| • Yes |
| • No |
| • We are unfamiliar with these concepts |

### Question 5.

| Do any of the following positions exist in your enterprise structure? | | | |
|---|---|---|---|
| | Yes | No | Don't know |
| Statistician / Data engineer | | | |
| Machine learning engineer / AI developer | | | |
| Data scientist | | | |
| AI project manager | | | |
| Data protection officer | | | |
| AI risk manager / AI ethics officer / Digital trust and safety officer or equivalent | | | |
| Other position/title with responsibilities for AI | | | |
| Chief information officer / Chief digital officer or equivalent | | | |
| Chief AI officer | | | |
| Chief analytics officer / Chief data officer / Head of data science or equivalent | | | |

Question 6.

| In the past 12 months, have any of the following conditions limited the use of cloud computing in your enterprise? | | | |
|---|---|---|---|
| | Yes | No | Don't know |
| High cost of retooling systems | | | |
| Concerns about corporate compliance | | | |
| Concerns about customisation of applications | | | |
| Concerns about network stability | | | |
| Lack of availability of cloud computing services | | | |
| Do not see the advantages of cloud computing | | | |
| Lack of support from top management | | | |
| Lack of IT skills | | | |
| The enterprise uses cloud computing without difficulty | | | |

Question 7.

| In the past 12 months, has your enterprise implemented any of the following practices to develop artificial intelligence? | | |
|---|---|---|
| | Yes | No |
| Training employees | | |
| Hiring new staff | | |
| R&D on artificial intelligence to use by the enterprise | | |
| Purchase of off-the-shelf software or hardware, or through business advisory services such as consultancy | | |
| Use of customised systems built by third parties | | |
| Created a senior management role or a team with responsibilities for artificial intelligence | | |
| Partnership with a national or international enterprise with capacities in artificial intelligence | | |

Question 8.

| In the past 12 months, has your enterprise used any of the following services provided by the public sector to support the adoption of artificial intelligence? | | |
|---|---|---|
| | Yes | No |
| Services that provide access to information or advice | | |
| Training services | | |
| Services that promote access to finance, such as subsidies or credit guarantees | | |

Question 9.

| In the past 12 months, has your enterprise established collaborations to develop artificial intelligence … | | |
|---|---|---|
| | Yes | No |
| With university faculty members, PhD or postdoctoral students? | | |
| With undergraduate students? | | |

| | | |
|---|---|---|
| With researchers in public research organisations? | | |
| With other partners? | | |

Question 10.

| In the past 12 months, have any of the following obstacles limited your enterprise in implementing artificial intelligence applications? | | |
|---|---|---|
| | Yes | No |
| Difficulties estimating the returns on investment in AI applications | | |
| Concerns related to data privacy, data protection or data security | | |
| Scarcity of cloud computing solutions that guarantee data security and regulatory compliance | | |
| Lack of clarity about the legal consequences in case of damage caused by the use of AI | | |
| Lack of vendors of AI systems offering solutions tailored to your enterprise's needs | | |
| Lack of external finance for investment to support AI adoption | | |
| Reluctance of staff to adopt AI | | |
| Difficulties to retrain or upskill staff | | |

Question 11.

| In the past 12 months, has your enterprise recruited graduates in artificial intelligence, machine learning or related fields? |
|---|
| • Yes, we were able to hire for our vacancies |
| • No, we could not hire appropriate candidates |
| • No, because we did not have specific vacancies |

Question 12.

| In the past 12 months, has your enterprise experienced difficulties in understanding what skill sets to look for in new AI recruits? |
|---|
| • Yes |
| • No |

Question 13.

| How would you say the following types of support could be for your enterprise to strengthen staff skills in AI? | | | | |
|---|---|---|---|---|
| | Very useful | Moderately useful | Slightly useful | Not useful at all |
| Partnerships with educational and vocational institutions | | | | |
| Tax allowances or tax credits for training in AI | | | | |
| Support to develop qualification frameworks for graduates in the field of AI | | | | |

Question 14.

| In using AI in your enterprise, how helpful would the following types of services provided by the public sector be? | | | | |
|---|---|---|---|---|
| | Very helpful | Helpful | A little helpful | Not helpful at all |
| Information on and examples of business use cases in your industry | | | | |
| Information on expected rates of return to investments in AI | | | | |
| Information on available and reliable technology vendors | | | | |
| Information on available and reliable sources of private-sector advice and expertise | | | | |
| Certification or accreditation schemes for AI solution providers | | | | |
| Information on current or forthcoming regulations around data or AI | | | | |

Question 15.

| How helpful would you say the following initiatives provided by the public sector could be for the adoption of AI in your enterprise? | | | | |
|---|---|---|---|---|
| | Very helpful | Helpful | A little helpful | Not helpful at all |
| Investing in university education and vocational training in fields related to AI | | | | |
| Investing in retraining and lifelong learning for employees who work with AI | | | | |
| Improving understanding of AI among government officials | | | | |
| Gathering and publishing administrative public datasets | | | | |
| Promoting a competitive AI vendor market | | | | |
| Upgrading IT infrastructure, such as high-speed broadband | | | | |

Question 16.

| Some uses of AI that involve autonomous systems might be detrimental to clients, potentially exposing businesses to legal jeopardy. Would you favour regulation that helps to overcome such a problem by establishing clear accountability when AI is used? |
|---|
| • Yes |
| • No |

Question 17.

| Are any of the following criteria important for your enterprise when developing or using AI applications? | | | | |
|---|---|---|---|---|
| | Strongly agree | Agree | Disagree | Strongly disagree |
| The protection of customer data and privacy | | | | |
| Making our customers aware of how our AI system(s) are developed, trained and used | | | | |
| Keeping a full record of our AI applications' predictions, recommendations or decisions | | | | |

Question 18.

| Are you aware that some regulators are considering the following requirements to increase oversight of artificial intelligence applications? | | |
|---|---|---|
| | Yes | No |
| Certification of the safety of AI systems | | |
| Notification for customers when decision making is automated | | |

Question 19.

| Approximately what percentage of your enterprise's total spending (internal and external) on R&D in 2019 was related to artificial intelligence? |
|---|
| • The enterprise does not spend on R&D |
| • 0% |
| • Between 1 % and 10% |
| • Between 11% and 30% |
| • More than 30% |
| • Cannot discuss |

# Annex D. Implementation and the survey's statistical features and limitations

## Finding the sample

A survey administration company conducted the survey. It drew on two proprietary global databases of experts. Together, these contain information on more than 1 million professionals globally. Together, the databases hold information on the company where the experts are currently employed, companies where the experts were previously employed, dates of employment at each company, job titles and job functions at each company, the country and city where the expert was employed with each company, the size of the companies where each expert was employed, and their areas of expertise.

The approach to identifying survey respondents was to filter the databases for executive candidates by the parameters of country, industry, job title and function. Note that the goal of filtering by job title and function was to find respondents who had a good understanding of how artificial intelligence (AI) is being used or is planned to be used in different parts of the enterprises they work in. The job titles searched were: statistician, data engineer, machine learning engineer, AI developer, data scientist, AI project manager, chief information officer, chief technology officer, chief digital officer, chief AI officer, chief data officer, head of data science or equivalent, chief analytics officer, IT manager, data protection officer, AI risk manager, AI ethics officer, digital trust and safety officer or equivalent, other position or any title with responsibilities for AI.

This initial selection of potential survey respondents yielded details of 12 026 experts in relevant fields in companies across the Group of Seven (G7) countries and target sectors. Enterprises were found by finding executives. It was not known how the distribution of enterprises in the databases relates statistically to distributions in the entire population of enterprises in each country.

From the lists of possible survey respondents in each country, the survey administration company randomly selected a subset of names to approach, the aim being to search for qualifying enterprises (e.g. active users of AI) and experts who agreed to participate in the survey. This search process would continue until the sample of 120 enterprises and satisfactorily completed surveys in each country, with the desired enterprise size and sectoral breakdowns, was had. The survey was conducted through a hybrid sampling approach (on line and CATI [Computer Assisted Telephone Interviewing]).

### *Method 1: Online portal survey*

Each expert was emailed with an invitation to take part in the survey. In the invitation email, they were first provided information on the desired expertise and current executive functions the respondent should have. They were also informed of the expected time needed to complete the survey questionnaire. At this stage, experts were not provided with a detailed overview of the survey content. Rather, the invitation provided generic information on the study's objective, namely, to gain insights into the process of AI adoption across various industries.

The invitation email contained a direct link to the survey. Respondents clicked on the link to the survey and completed it without outside guidance or support.

Once an expert was invited to participate in the survey, an automated system sent reminders at intervals of 24 hours. Each expert received a maximum of two reminders, regardless of whether they had already started the survey or had not responded or engaged with it at all. As noted above, this process continued until the desired number of satisfactorily completed questionnaires was achieved.

### *Method 2: CATI survey*

The CATI methodology involves a moderator calling the respondent and taking them through the survey step by step. The moderator reads each question to the respondent and types their answers into the survey for them.

Potential respondents were initially invited by email to participate in the survey, as described above. The details of candidates agreeing to be surveyed were uploaded into a CATI dialler, through which the scheduling team reached out to respondents to book interviews. The scheduling team pre-screened the experts using the following prompt: "Kindly confirm whether you are knowledgeable enough about the usage of artificial intelligence in different parts of your enterprise and have a fair understanding about the scope and challenges pertaining to the usage of AI within your organisation."

### *Piloting and full-scale survey administration*

The survey was administered in two phases: 1) a pilot; and 2) full-scale administration. The pilot's goal was to ensure ease of use of the survey and to ensure no errors were introduced during the programming of the survey questions. Nine enterprises completed the pilot stage. A review of the responses determined that the survey was correctly coded. Based on this validation, it was concluded that the survey questionnaire required no changes or corrective actions.

Throughout the administration of the survey, the online expert network provider monitored all responses daily to implement quality checks that ensured experts were not speeding through the questionnaire. The results from respondents who spent less than six minutes on the survey were removed. In addition, results from respondents who straight-lined grid-type questions were removed. During the process, the administrator closely monitored open-ended questions to ensure they aligned with the question being asked. During the process, 288 survey responses were deemed of insufficient quality and removed.

The entire process, beginning with the identification of the initial set of 12 026 potential respondents and receipt of the final acceptably completed questionnaire, took place from 5 November 2022 to 6 January 2023. Of the 840 final responses, 353 (42%) were obtained through the CATI process, the remainder coming from the online completions.

## Statistical limitations

Several limitations must be considered concerning the results of the current study. First, the descriptive results and the underlying sample do not represent the firms' population in each country. In other words, the results in the current study relate to averages among the surveyed firms. They are not directly generalisable to the respective population of firms within a given country. One reason for this lack of generalisability is that this study does not use sampling weights to correct for the actual distribution of firms with respect to sector or size. For instance, the population of enterprises in all countries is characterised by the fact that the number of medium-sized enterprises (50-249 employees) is significantly higher than the number of large enterprises (≥ 250 employees), which is not taken into account in this study by using weights. Therefore, any result that does not directly differentiate between enterprise size classes – i.e. either by controlling for size class in a regression analysis or presenting statistics for each size class separately – will be skewed towards large enterprises, as compared to a representative result for the population of firms.

Another caveat with respect to the generalisation stems from the sampling procedure. Instead of conducting probability sampling among the population of enterprises in a given country, the survey provider primarily contacted enterprises with a high probability of being AI users. Thus, the sampling frame used by the survey provider was not a random subset of enterprises in each country. As a result, the underlying sample for the current study is not a random sample of AI-using enterprises but rather a selection of AI-using enterprises out of a pool of enterprises with a high probability of being AI users. As discussed by Stantcheva (2022[1]), "non-probability sampling, such as the quota sampling performed by survey companies, carries risks in terms of representativeness." However, as the sampling procedure did not differ systematically between countries, this bias is less likely to affect the comparability of the results across countries in the current study.

A second limitation of the study arises from the number of observations. On the one hand, the total of 840 AI-using enterprises is a significantly higher number of observations than most studies of AI-using enterprises. On the other hand, the analysis covers seven countries, two sectors, and two enterprise size classes. Therefore, any breakdown by those dimensions rapidly decreases the sample size to produce statistically precise approximations of the true population parameters (even if sampling weights and a representative sample had been used). Since the total number of 840 observations was fixed due to budget constraints, the following approach was used to maximise the statistical power of the analyses among G7 countries. Given the available number of 120 observations per country, it was first decided that, at most, 2 strata should be used in the sampling procedure with a total number of 30 observations per cell (see the following paragraph for a discussion of the statistical properties of such sample sizes). Analyses at this granular level with 30 observations, however, are not published in this study. To stratify the sample is an important step to allow for statistical analyses of pre-defined groups of interest within the target population.

There is no formula to determine what sample size qualifies as "sufficiently large". A general rule of thumb used by many academic publications and often taught in statistics courses is 30. There are several reasons for this number, e.g. it is seen as the lower bound for the central limited theorem (CLT) to hold and 30 observations are generally seen as a good balance between maximising the sample size (and hence statistical precision) and cost efficiency (the CLT refers to the fact that regardless of the shape of the original population distribution [which might be unknown], the sampling distribution of the sample mean will approximate a normal distribution as the sample size increases. This holds true, provided the sample size is sufficiently large).

This rule of thumb is not only applied by academics and researchers but has repeatedly been used in the context of policy advice as well as publications by governmental and non-governmental institutions. However, the number 30 is not engraved in stone but can be slightly adapted. A working paper by the European Central Bank (ECB) chose a threshold of 20 observations as they decided that "[d]ue to confidentiality constraints, less than 20 observations per cell at the sector level were dropped" (ECB, 2014[2]). Eurostat's 1990 poverty report was stricter, stating that "[i]f the number of observations per cell is below 50 households, the estimates relating to that cell are considered unreliable and will not be presented in the tables" (Eurostat, 1990, p. 38[3]). Another practical example is the guidelines from the Bundesamt für Statistik, the Federal Office for Statistics in Switzerland. According to these, comparisons that rely on cells with fewer than 10 observations must not be published, and comparisons based on cell frequencies of 10-29 observations must be accompanied by a note concerning the reduced statistical reliability of the results (BASS, 2016, p. 131[4]). Moreover, in Germany, the widely used "Mietspiegel" (rent index) is officially required by the Federal Office for Building and Regional Planning (BBR) to use at least 30 apartments per cell in order to publish reliable information on average rental prices (BBR, 2020[5]).

## References

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# Annex E. Aggregated responses to the 2022-23 OECD/BCG/INSEAD Survey of AI-Adopting Enterprises

### Table E.1. Q1 - How important are AI applications to your enterprise's core business processes?

| Country | Enterprise size | Sector | Critically important | Of minor importance | One among a number of important considerations |
|---|---|---|---|---|---|
| CAN | 50-249 | ICT | 19 (63.3%) | 0 (0.0%) | 11 (36.7%) |
| | | Manufacturing | 22 (73.3%) | 2 (6.7%) | 6 (20.0%) |
| | 250+ | ICT | 16 (53.3%) | 1 (3.3%) | 13 (43.3%) |
| | | Manufacturing | 9 (30.0%) | 9 (30.0%) | 12 (40.0%) |
| DEU | 50-249 | ICT | 17 (56.7%) | 0 (0.0%) | 13 (43.3%) |
| | | Manufacturing | 13 (43.3%) | 4 (13.3%) | 13 (43.3%) |
| | 250+ | ICT | 21 (70.0%) | 1 (3.3%) | 8 (26.7%) |
| | | Manufacturing | 4 (13.3%) | 6 (20.0%) | 20 (66.7%) |
| FRA | 50-249 | ICT | 21 (70.0%) | 0 (0.0%) | 9 (30.0%) |
| | | Manufacturing | 26 (86.7%) | 0 (0.0%) | 4 (13.3%) |
| | 250+ | ICT | 18 (60.0%) | 0 (0.0%) | 12 (40.0%) |
| | | Manufacturing | 15 (50.0%) | 1 (3.3%) | 14 (46.7%) |
| GBR | 50-249 | ICT | 20 (66.7%) | 1 (3.3%) | 9 (30.0%) |
| | | Manufacturing | 18 (60.0%) | 5 (16.7%) | 7 (23.3%) |
| | 250+ | ICT | 16 (53.3%) | 0 (0.0%) | 14 (46.7%) |
| | | Manufacturing | 8 (26.7%) | 3 (10.0%) | 19 (63.3%) |
| ITA | 50-249 | ICT | 14 (46.7%) | 0 (0.0%) | 16 (53.3%) |
| | | Manufacturing | 10 (33.3%) | 8 (26.7%) | 12 (40.0%) |
| | 250+ | ICT | 19 (63.3%) | 1 (3.3%) | 10 (33.3%) |
| | | Manufacturing | 9 (30.0%) | 6 (20.0%) | 15 (50.0%) |
| JPN | 50-249 | ICT | 19 (63.3%) | 0 (0.0%) | 11 (36.7%) |
| | | Manufacturing | 22 (73.3%) | 3 (10.0%) | 5 (16.7%) |
| | 250+ | ICT | 25 (83.3%) | 0 (0.0%) | 5 (16.7%) |
| | | Manufacturing | 17 (56.7%) | 1 (3.3%) | 12 (40.0%) |
| USA | 50-249 | ICT | 19 (63.3%) | 0 (0.0%) | 11 (36.7%) |
| | | Manufacturing | 9 (30.0%) | 8 (26.7%) | 13 (43.3%) |
| | 250+ | ICT | 12 (40.0%) | 1 (3.3%) | 17 (56.7%) |
| | | Manufacturing | 8 (26.7%) | 3 (10.0%) | 19 (63.3%) |

## Table E.2. Q2 - In approximately which year was your enterprise incorporated?

| Country | Enterprise size | Sector | 1950 or earlier | 1950-1960 | 1960-1970 | 1970-1980 | 1980-1990 | 1990-2000 | 2000-2010 | 2010-2020 | After 2020 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CAN | 50-249 | ICT | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) | 2 (6.7%) | 3 (10.0%) | 4 (13.3%) | 13 (43.3%) | 8 (26.7%) | 0 (0.0%) |
| | | Manufacturing | 1 (3.3%) | 0 (0.0%) | 1 (3.3%) | 1 (3.3%) | 0 (0.0%) | 7 (23.3%) | 8 (26.7%) | 12 (40.0%) | 0 (0.0%) |
| | 250+ | ICT | 1 (3.3%) | 3 (10.0%) | 0 (0.0%) | 1 (3.3%) | 2 (6.7%) | 4 (13.3%) | 13 (43.3%) | 6 (20.0%) | 0 (0.0%) |
| | | Manufacturing | 4 (13.3%) | 1 (3.3%) | 2 (6.7%) | 4 (13.3%) | 4 (13.3%) | 9 (30.0%) | 4 (13.3%) | 2 (6.7%) | 0 (0.0%) |
| DEU | 50-249 | ICT | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 7 (23.3%) | 15 (50.0%) | 7 (23.3%) | 0 (0.0%) |
| | | Manufacturing | 2 (6.7%) | 0 (0.0%) | 2 (6.7%) | 0 (0.0%) | 1 (3.3%) | 12 (40.0%) | 9 (30.0%) | 3 (10.0%) | 1 (3.3%) |
| | 250+ | ICT | 1 (3.3%) | 0 (0.0%) | 5 (16.7%) | 1 (3.3%) | 7 (23.3%) | 6 (20.0%) | 2 (6.7%) | 6 (20.0%) | 2 (6.7%) |
| | | Manufacturing | 14 (46.7%) | 1 (3.3%) | 1 (3.3%) | 2 (6.7%) | 3 (10.0%) | 3 (10.0%) | 4 (13.3%) | 2 (6.7%) | 0 (0.0%) |
| FRA | 50-249 | ICT | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 1 (3.3%) | 9 (30.0%) | 7 (23.3%) | 7 (23.3%) | 5 (16.7%) | 0 (0.0%) |
| | | Manufacturing | 1 (3.3%) | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 8 (26.7%) | 8 (26.7%) | 12 (40.0%) | 0 (0.0%) |
| | 250+ | ICT | 2 (6.7%) | 0 (0.0%) | 1 (3.3%) | 1 (3.3%) | 6 (20.0%) | 6 (20.0%) | 5 (16.7%) | 9 (30.0%) | 0 (0.0%) |
| | | Manufacturing | 4 (13.3%) | 1 (3.3%) | 3 (10.0%) | 4 (13.3%) | 4 (13.3%) | 3 (10.0%) | 4 (13.3%) | 5 (16.7%) | 2 (6.7%) |
| GBR | 50-249 | ICT | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 7 (23.3%) | 4 (13.3%) | 3 (10.0%) | 8 (26.7%) | 7 (23.3%) | 0 (0.0%) |
| | | Manufacturing | 3 (10.0%) | 1 (3.3%) | 2 (6.7%) | 4 (13.3%) | 6 (20.0%) | 0 (0.0%) | 6 (20.0%) | 7 (23.3%) | 1 (3.3%) |
| | 250+ | ICT | 5 (16.7%) | 1 (3.3%) | 0 (0.0%) | 1 (3.3%) | 7 (23.3%) | 8 (26.7%) | 3 (10.0%) | 5 (16.7%) | 0 (0.0%) |
| | | Manufacturing | 10 (33.3%) | 3 (10.0%) | 2 (6.7%) | 3 (10.0%) | 4 (13.3%) | 3 (10.0%) | 2 (6.7%) | 3 (10.0%) | 0 (0.0%) |
| ITA | 50-249 | ICT | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) | 2 (6.7%) | 2 (6.7%) | 8 (26.7%) | 11 (36.7%) | 7 (23.3%) | 0 (0.0%) |
| | | Manufacturing | 4 (13.3%) | 2 (6.7%) | 2 (6.7%) | 4 (13.3%) | 4 (13.3%) | 5 (16.7%) | 6 (20.0%) | 3 (10.0%) | 0 (0.0%) |
| | 250+ | ICT | 1 (3.3%) | 0 (0.0%) | 0 (0.0%) | 3 (10.0%) | 8 (26.7%) | 9 (30.0%) | 5 (16.7%) | 4 (13.3%) | 0 (0.0%) |
| | | Manufacturing | 7 (23.3%) | 1 (3.3%) | 3 (10.0%) | 2 (6.7%) | 1 (3.3%) | 5 (16.7%) | 3 (10.0%) | 7 (23.3%) | 1 (3.3%) |
| JPN | 50-249 | ICT | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 3 (10.0%) | 4 (13.3%) | 9 (30.0%) | 7 (23.3%) | 6 (20.0%) | 0 (0.0%) |
| | | Manufacturing | 5 (16.7%) | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 2 (6.7%) | 2 (6.7%) | 12 (40.0%) | 8 (26.7%) | 0 (0.0%) |
| | 250+ | ICT | 3 (10.0%) | 1 (3.3%) | 3 (10.0%) | 4 (13.3%) | 6 (20.0%) | 4 (13.3%) | 3 (10.0%) | 6 (20.0%) | 0 (0.0%) |
| | | Manufacturing | 13 (43.3%) | 5 (16.7%) | 1 (3.3%) | 2 (6.7%) | 1 (3.3%) | 4 (13.3%) | 4 (13.3%) | 0 (0.0%) | 0 (0.0%) |
| USA | 50-249 | ICT | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) | 4 (13.3%) | 5 (16.7%) | 19 (63.3%) | 1 (3.3%) |
| | | Manufacturing | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) | 0 (0.0%) | 3 (10.0%) | 8 (26.7%) | 7 (23.3%) | 10 (33.3%) | 1 (3.3%) |
| | 250+ | ICT | 0 (0.0%) | 0 (0.0%) | 1 (3.3%) | 2 (6.7%) | 3 (10.0%) | 6 (20.0%) | 6 (20.0%) | 12 (40.0%) | 0 (0.0%) |
| | | Manufacturing | 9 (30.0%) | 3 (10.0%) | 1 (3.3%) | 3 (10.0%) | 4 (13.3%) | 2 (6.7%) | 2 (6.7%) | 5 (16.7%) | 1 (3.3%) |

## Table E.3. Q3 - In the past 12 months, has your enterprise collected or otherwise acquired data from any of the following sources?

| Country | Enterprise size | Sector | Data collected internally from processes and staff | | Data collected from customers and users | | Data from private data providers, such as organisations dedicated to producing and selling data | | Data from a partner enterprise | | Data from a research institute | | Data from the public sector | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| CAN | 50-249 | ICT | 11 (36.7%) | 19 (63.3%) | 6 (20.0%) | 24 (80.0%) | 13 (43.3%) | 17 (56.7%) | 12 (40.0%) | 18 (60.0%) | 14 (46.7%) | 16 (53.3%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 7 (23.3%) | 23 (76.7%) | 6 (20.0%) | 24 (80.0%) | 14 (46.7%) | 16 (53.3%) | 14 (46.7%) | 16 (53.3%) | 13 (43.3%) | 17 (56.7%) | 13 (43.3%) | 17 (56.7%) |
| | 250+ | ICT | 8 (26.7%) | 22 (73.3%) | 4 (13.3%) | 26 (86.7%) | 12 (40.0%) | 18 (60.0%) | 16 (53.3%) | 14 (46.7%) | 16 (53.3%) | 14 (46.7%) | 10 (33.3%) | 20 (66.7%) |
| | | MFT | 12 (40.0%) | 18 (60.0%) | 10 (33.3%) | 20 (66.7%) | 10 (33.3%) | 20 (66.7%) | 13 (43.3%) | 17 (56.7%) | 17 (56.7%) | 13 (43.3%) | 19 (63.3%) | 11 (36.7%) |
| DEU | 50-249 | ICT | 6 (20.0%) | 24 (80.0%) | 11 (36.7%) | 19 (63.3%) | 10 (33.3%) | 20 (66.7%) | 19 (63.3%) | 11 (36.7%) | 19 (63.3%) | 11 (36.7%) | 18 (60.0%) | 12 (40.0%) |
| | | MFT | 5 (17.2%) | 24 (82.8%) | 10 (34.5%) | 19 (65.5%) | 13 (44.8%) | 16 (55.2%) | 13 (44.8%) | 16 (55.2%) | 10 (34.5%) | 19 (65.5%) | 12 (41.4%) | 17 (58.6%) |
| | 250+ | ICT | 10 (33.3%) | 20 (66.7%) | 6 (20.0%) | 24 (80.0%) | 14 (46.7%) | 16 (53.3%) | 10 (33.3%) | 20 (66.7%) | 20 (66.7%) | 10 (33.3%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 8 (26.7%) | 22 (73.3%) | 7 (23.3%) | 23 (76.7%) | 14 (46.7%) | 16 (53.3%) | 14 (46.7%) | 16 (53.3%) | 12 (40.0%) | 18 (60.0%) | 17 (56.7%) | 13 (43.3%) |
| FRA | 50-249 | ICT | 11 (36.7%) | 19 (63.3%) | 13 (43.3%) | 17 (56.7%) | 15 (50.0%) | 15 (50.0%) | 8 (26.7%) | 22 (73.3%) | 14 (46.7%) | 16 (53.3%) | 14 (46.7%) | 16 (53.3%) |
| | | MFT | 1 (3.3%) | 29 (96.7%) | 3 (10.0%) | 27 (90.0%) | 15 (50.0%) | 15 (50.0%) | 10 (33.3%) | 20 (66.7%) | 9 (30.0%) | 21 (70.0%) | 13 (43.3%) | 17 (56.7%) |
| | 250+ | ICT | 8 (26.7%) | 22 (73.3%) | 4 (13.3%) | 26 (86.7%) | 16 (53.3%) | 14 (46.7%) | 13 (43.3%) | 17 (56.7%) | 14 (46.7%) | 16 (53.3%) | 13 (43.3%) | 17 (56.7%) |
| | | MFT | 8 (26.7%) | 22 (73.3%) | 6 (20.0%) | 24 (80.0%) | 13 (43.3%) | 17 (56.7%) | 11 (36.7%) | 19 (63.3%) | 13 (43.3%) | 17 (56.7%) | 15 (50.0%) | 15 (50.0%) |
| GBR | 50-249 | ICT | 8 (26.7%) | 22 (73.3%) | 6 (20.0%) | 24 (80.0%) | 12 (40.0%) | 18 (60.0%) | 15 (50.0%) | 15 (50.0%) | 14 (46.7%) | 16 (53.3%) | 13 (43.3%) | 17 (56.7%) |
| | | MFT | 6 (20.0%) | 24 (80.0%) | 9 (30.0%) | 21 (70.0%) | 8 (26.7%) | 22 (73.3%) | 13 (43.3%) | 17 (56.7%) | 15 (50.0%) | 15 (50.0%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 3 (10.0%) | 27 (90.0%) | 6 (20.0%) | 24 (80.0%) | 7 (23.3%) | 23 (76.7%) | 12 (40.0%) | 18 (60.0%) | 15 (50.0%) | 15 (50.0%) | 10 (33.3%) | 20 (66.7%) |
| | | MFT | 5 (16.7%) | 25 (83.3%) | 9 (30.0%) | 21 (70.0%) | 12 (40.0%) | 18 (60.0%) | 12 (40.0%) | 18 (60.0%) | 14 (46.7%) | 16 (53.3%) | 11 (36.7%) | 19 (63.3%) |
| ITA | 50-249 | ICT | 6 (20.0%) | 24 (80.0%) | 11 (36.7%) | 19 (63.3%) | 17 (56.7%) | 13 (43.3%) | 18 (60.0%) | 12 (40.0%) | 12 (40.0%) | 18 (60.0%) | 18 (60.0%) | 12 (40.0%) |
| | | MFT | 7 (23.3%) | 23 (76.7%) | 14 (46.7%) | 16 (53.3%) | 17 (56.7%) | 13 (43.3%) | 11 (36.7%) | 19 (63.3%) | 15 (50.0%) | 15 (50.0%) | 18 (60.0%) | 12 (40.0%) |
| | 250+ | ICT | 6 (20.0%) | 24 (80.0%) | 12 (40.0%) | 18 (60.0%) | 13 (43.3%) | 17 (56.7%) | 13 (43.3%) | 17 (56.7%) | 15 (50.0%) | 15 (50.0%) | 12 (40.0%) | 18 (60.0%) |
| | | MFT | 11 (36.7%) | 19 (63.3%) | 10 (33.3%) | 20 (66.7%) | 13 (43.3%) | 17 (56.7%) | 19 (63.3%) | 11 (36.7%) | 11 (36.7%) | 19 (63.3%) | 16 (53.3%) | 14 (46.7%) |
| JPN | 50-249 | ICT | 2 (6.7%) | 28 (93.3%) | 9 (30.0%) | 21 (70.0%) | 11 (36.7%) | 19 (63.3%) | 12 (40.0%) | 18 (60.0%) | 20 (66.7%) | 10 (33.3%) | 22 (73.3%) | 8 (26.7%) |
| | | MFT | 3 (10.0%) | 27 (90.0%) | 8 (26.7%) | 22 (73.3%) | 9 (30.0%) | 21 (70.0%) | 6 (20.0%) | 24 (80.0%) | 12 (40.0%) | 18 (60.0%) | 16 (53.3%) | 14 (46.7%) |
| | 250+ | ICT | 7 (23.3%) | 23 (76.7%) | 9 (30.0%) | 21 (70.0%) | 11 (36.7%) | 19 (63.3%) | 13 (43.3%) | 17 (56.7%) | 15 (50.0%) | 15 (50.0%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 5 (16.7%) | 25 (83.3%) | 7 (23.3%) | 23 (76.7%) | 8 (26.7%) | 22 (73.3%) | 14 (46.7%) | 16 (53.3%) | 11 (36.7%) | 19 (63.3%) | 14 (46.7%) | 16 (53.3%) |

| Country | Enterprise size | Sector | Data collected internally from processes and staff | | Data collected from customers and users | | Data from private data providers, such as organisations dedicated to producing and selling data | | Data from a partner enterprise | | Data from a research institute | | Data from the public sector | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| USA | 50-249 | ICT | 8 (27.6%) | 21 (72.4%) | 3 (10.3%) | 26 (89.7%) | 8 (27.6%) | 21 (72.4%) | 12 (41.4%) | 17 (58.6%) | 13 (44.8%) | 16 (55.2%) | 12 (41.4%) | 17 (58.6%) |
| | | MFT | 11 (36.7%) | 19 (63.3%) | 8 (26.7%) | 22 (73.3%) | 7 (23.3%) | 23 (76.7%) | 13 (43.3%) | 17 (56.7%) | 16 (53.3%) | 14 (46.7%) | 16 (53.3%) | 14 (46.7%) |
| | 250+ | ICT | 2 (6.7%) | 28 (93.3%) | 3 (10.0%) | 27 (90.0%) | 12 (40.0%) | 18 (60.0%) | 11 (36.7%) | 19 (63.3%) | 17 (56.7%) | 13 (43.3%) | 13 (43.3%) | 17 (56.7%) |
| | | MFT | 3 (10.0%) | 27 (90.0%) | 3 (10.0%) | 27 (90.0%) | 9 (30.0%) | 21 (70.0%) | 13 (43.3%) | 17 (56.7%) | 12 (40.0%) | 18 (60.0%) | 14 (46.7%) | 16 (53.3%) |

Note: MFT = Manufacturing.

## Table E.4. Q4 - Does your enterprise use a data management solution, such as a data lake?

| Country | Enterprise size | Sector | No | We are unfamiliar with this concept | Yes |
|---|---|---|---|---|---|
| CAN | 50-249 | ICT | 7 (23.3%) | 0 (0.0%) | 23 (76.7%) |
| | | Manufacturing | 5 (16.7%) | 0 (0.0%) | 25 (83.3%) |
| | 250+ | ICT | 4 (13.3%) | 0 (0.0%) | 26 (86.7%) |
| | | Manufacturing | 15 (50.0%) | 0 (0.0%) | 15 (50.0%) |
| DEU | 50-249 | ICT | 2 (6.7%) | 0 (0.0%) | 28 (93.3%) |
| | | Manufacturing | 14 (46.7%) | 0 (0.0%) | 16 (53.3%) |
| | 250+ | ICT | 2 (6.7%) | 0 (0.0%) | 28 (93.3%) |
| | | Manufacturing | 12 (40.0%) | 0 (0.0%) | 18 (60.0%) |
| FRA | 50-249 | ICT | 3 (10.0%) | 0 (0.0%) | 27 (90.0%) |
| | | Manufacturing | 2 (6.7%) | 0 (0.0%) | 28 (93.3%) |
| | 250+ | ICT | 0 (0.0%) | 1 (3.3%) | 29 (96.7%) |
| | | Manufacturing | 5 (16.7%) | 0 (0.0%) | 25 (83.3%) |
| GBR | 50-249 | ICT | 5 (16.7%) | 0 (0.0%) | 25 (83.3%) |
| | | Manufacturing | 11 (36.7%) | 0 (0.0%) | 19 (63.3%) |
| | 250+ | ICT | 3 (10.0%) | 0 (0.0%) | 27 (90.0%) |
| | | Manufacturing | 9 (30.0%) | 0 (0.0%) | 21 (70.0%) |
| ITA | 50-249 | ICT | 9 (30.0%) | 0 (0.0%) | 21 (70.0%) |
| | | Manufacturing | 13 (43.3%) | 0 (0.0%) | 17 (56.7%) |
| | 250+ | ICT | 1 (3.3%) | 0 (0.0%) | 29 (96.7%) |
| | | Manufacturing | 11 (36.7%) | 0 (0.0%) | 19 (63.3%) |
| JPN | 50-249 | ICT | 6 (20.0%) | 0 (0.0%) | 24 (80.0%) |
| | | Manufacturing | 6 (20.0%) | 0 (0.0%) | 24 (80.0%) |
| | 250+ | ICT | 3 (10.0%) | 0 (0.0%) | 27 (90.0%) |
| | | Manufacturing | 7 (23.3%) | 2 (6.7%) | 21 (70.0%) |
| USA | 50-249 | ICT | 5 (16.7%) | 0 (0.0%) | 25 (83.3%) |
| | | Manufacturing | 17 (56.7%) | 2 (6.7%) | 11 (36.7%) |
| | 250+ | ICT | 1 (3.3%) | 0 (0.0%) | 29 (96.7%) |
| | | Manufacturing | 2 (6.7%) | 1 (3.3%) | 27 (90.0%) |

## Table E.5. Q5 - Do any of the following positions exist in your enterprise structure?

If some roles overlap and/or some employees take on multiple roles, please only count them once

| Country | Enterprise size | Sector | Statistician / Data engineer | | | Machine learning engineer / AI developer | | | Data scientist | | | AI project manager | | | Data protection officer | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| CAN | 50-249 | ICT | 0 (0.0) | 5 (16.7) | 25 (83.3) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 22 (73.3) | 8 (26.7) | 0 (0.0) | 12 (40.0) | 18 (60.0) |
| | | MFT | 0 (0.0) | 2 (6.7) | 28 (93.3) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 0 (0.0) | 13 (43.3) | 17 (56.7) |
| | 250+ | ICT | 0 (0.0) | 4 (13.3) | 26 (86.7) | 1 (3.3) | 6 (20.0) | 23 (76.7) | 2 (6.7) | 6 (20.0) | 22 (73.3) | 1 (3.3) | 16 (53.3) | 13 (43.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) |
| | | MFT | 1 (3.3) | 12 (40.0) | 17 (56.7) | 1 (3.3) | 13 (43.3) | 16 (53.3) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 1 (3.3) | 17 (56.7) | 12 (40.0) |
| DEU | 50-249 | ICT | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 17 (56.7) | 13 (43.3) |
| | | MFT | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 13 (43.3) | 17 (56.7) | 1 (3.3) | 7 (23.3) | 22 (73.3) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) |
| | 250+ | ICT | 1 (3.3) | 3 (10.0) | 26 (86.7) | 1 (3.3) | 4 (13.3) | 25 (83.3) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 1 (3.3) | 12 (40.0) | 17 (56.7) | 1 (3.3) | 15 (50.0) | 14 (46.7) |
| | | MFT | 0 (0.0) | 3 (10.0) | 27 (90.0) | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 2 (6.7) | 11 (36.7) | 17 (56.7) | 0 (0.0) | 11 (36.7) | 19 (63.3) |
| FRA | 50-249 | ICT | 0 (0.0) | 5 (16.7) | 25 (83.3) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 12 (40.0) | 18 (60.0) |
| | | MFT | 0 (0.0) | 1 (3.3) | 29 (96.7) | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 5 (16.7) | 25 (83.3) | 1 (3.3) | 3 (10.0) | 26 (86.7) | 0 (0.0) | 11 (36.7) | 19 (63.3) |
| | 250+ | ICT | 0 (0.0) | 1 (3.3) | 29 (96.7) | 0 (0.0) | 2 (6.7) | 28 (93.3) | 0 (0.0) | 4 (13.3) | 26 (86.7) | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 7 (23.3) | 23 (76.7) |
| | | MFT | 0 (0.0) | 2 (6.7) | 28 (93.3) | 0 (0.0) | 4 (13.3) | 26 (86.7) | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 1 (3.3) | 8 (26.7) | 21 (70.0) |
| GBR | 50-249 | ICT | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 13 (43.3) | 17 (56.7) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 2 (6.7) | 16 (53.3) | 12 (40.0) |
| | | MFT | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 2 (6.7) | 4 (13.3) | 24 (80.0) |
| | 250+ | ICT | 0 (0.0) | 0 (0.0) | 30 (100) | 0 (0.0) | 2 (6.7) | 28 (93.3) | 2 (6.7) | 5 (16.7) | 23 (76.7) | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 8 (26.7) | 22 (73.3) |
| | | MFT | 0 (0.0) | 4 (13.3) | 26 (86.7) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 2 (6.7) | 4 (13.3) | 24 (80.0) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) |
| ITA | 50-249 | ICT | 0 (0.0) | 6 (20.0) | 24 (80.0) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 14 (46.7) | 16 (53.3) |
| | | MFT | 0 (0.0) | 7 (23.3) | 23 (76.7) | 1 (3.3) | 7 (23.3) | 22 (73.3) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 1 (3.3) | 19 (63.3) | 10 (33.3) |
| | 250+ | ICT | 0 (0.0) | 5 (16.7) | 25 (83.3) | 0 (0.0) | 6 (20.0) | 24 (80.0) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 10 (33.3) | 20 (66.7) |
| | | MFT | 0 (0.0) | 4 (13.3) | 26 (86.7) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) |
| JPN | 50-249 | ICT | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 2 (6.7) | 28 (93.3) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 0 (0.0) | 15 (50.0) | 15 (50.0) |
| | | MFT | 0 (0.0) | 10 (33.3) | 20 (66.7) | 4 (13.3) | 7 (23.3) | 19 (63.3) | 5 (16.7) | 7 (23.3) | 18 (60.0) | 2 (6.7) | 6 (20.0) | 22 (73.3) | 3 (10.0) | 13 (43.3) | 14 (46.7) |

| Country | Enterprise size | Sector | Statistician / Data engineer | | | Machine learning engineer / AI developer | | | Data scientist | | | AI project manager | | | Data protection officer | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| | 250+ | ICT | 0 (0.0) | 5 (16.7) | 25 (83.3) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 13 (43.3) | 17 (56.7) |
| | | MFT | 1 (3.3) | 10 (33.3) | 19 (63.3) | 1 (3.3) | 9 (30.0) | 20 (66.7) | 1 (3.3) | 5 (16.7) | 24 (80.0) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 4 (13.3) | 26 (86.7) |
| USA | 50-249 | ICT | 0 (0.0) | 1 (3.3) | 29 (96.7) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 4 (13.3) | 26 (86.7) | 0 (0.0) | 21 (70.0) | 9 (30.0) | 0 (0.0) | 20 (66.7) | 10 (33.3) |
| | | MFT | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 15 (50.0) | 15 (50.0) |
| | 250+ | ICT | 0 (0.0) | 1 (3.3) | 29 (96.7) | 0 (0.0) | 2 (6.7) | 28 (93.3) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 1 (3.3) | 12 (40.0) | 17 (56.7) |
| | | MFT | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 5 (16.7) | 25 (83.3) | 1 (3.3) | 6 (20.0) | 23 (76.7) | 0 (0.0) | 13 (43.3) | 17 (56.7) | 1 (3.3) | 11 (36.7) | 18 (60.0) |

Note: MFT = Manufacturing. Numbers presented in parentheses are percentages.

## Table E.6. Q5 - Do any of the following positions exist in your enterprise structure? (continued)

| Country | Enterprise size | Sector | AI risk manager / AI ethics officer / Digital trust and safety officer or equivalent | | | Other position/title with responsibilities for AI | | | Chief information officer / Chief digital officer or equivalent | | | Chief AI officer | | | Chief analytics officer / Chief data officer / Head of data science or equivalent | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| CAN | 50-249 | ICT | 1 (3.3) | 19 (63.3) | 10 (33.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 23 (76.7) | 7 (23.3) | 0 (0.0) | 15 (50.0) | 15 (50.0) |
| | | MFT | 0 (0.0) | 13 (43.3) | 17 (56.7) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 6 (20.0) | 24 (80.0) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 9 (30.0) | 21 (70.0) |
| | 250+ | ICT | 1 (3.3) | 16 (53.3) | 13 (43.3) | 4 (13.3) | 13 (43.3) | 13 (43.3) | 1 (3.3) | 6 (20.0) | 23 (76.7) | 1 (3.3) | 22 (73.3) | 7 (23.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) |
| | | MFT | 2 (6.7) | 21 (70.0) | 7 (23.3) | 3 (10.0) | 9 (30.0) | 18 (60.0) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 1 (3.3) | 26 (86.7) | 3 (10.0) | 0 (0.0) | 12 (40.0) | 18 (60.0) |
| DEU | 50-249 | ICT | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 24 (80.0) | 6 (20.0) | 0 (0.0) | 5 (16.7) | 25 (83.3) |
| | | MFT | 1 (3.3) | 13 (43.3) | 16 (53.3) | 3 (10.0) | 11 (36.7) | 16 (53.3) | 2 (6.7) | 9 (30.0) | 19 (63.3) | 3 (10.0) | 18 (60.0) | 9 (30.0) | 3 (10.0) | 10 (33.3) | 17 (56.7) |
| | 250+ | ICT | 1 (3.3) | 12 (40.0) | 17 (56.7) | 2 (6.7) | 10 (33.3) | 18 (60.0) | 1 (3.3) | 5 (16.7) | 24 (80.0) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 8 (26.7) | 22 (73.3) |
| | | MFT | 2 (6.7) | 16 (53.3) | 12 (40.0) | 5 (16.7) | 12 (40.0) | 13 (43.3) | 2 (6.7) | 5 (16.7) | 23 (76.7) | 2 (6.7) | 24 (80.0) | 4 (13.3) | 2 (6.7) | 14 (46.7) | 14 (46.7) |
| FRA | 50-249 | ICT | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 1 (3.3) | 9 (30.0) | 20 (66.7) |
| | | MFT | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 8 (26.7) | 22 (73.3) |
| | 250+ | ICT | 0 (0.0) | 12 (40.0) | 18 (60.0) | 2 (6.7) | 13 (43.3) | 15 (50.0) | 0 (0.0) | 0 (0.0) | 30 (100) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 0 (0.0) | 7 (23.3) | 23 (76.7) |
| | | MFT | 2 (6.7) | 10 (33.3) | 18 (60.0) | 4 (13.3) | 10 (33.3) | 16 (53.3) | 1 (3.3) | 1 (3.3) | 28 (93.3) | 1 (3.3) | 18 (60.0) | 11 (36.7) | 0 (0.0) | 8 (26.7) | 22 (73.3) |
| DEU | 50-249 | ICT | 5 (16.7) | 13 (43.3) | 12 (40.0) | 1 (3.3) | 17 (56.7) | 12 (40.0) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 2 (6.7) | 23 (76.7) | 5 (16.7) | 1 (3.3) | 12 (40.0) | 17 (56.7) |

| Country | Enterprise size | Sector | AI risk manager / AI ethics officer / Digital trust and safety officer or equivalent | | | Other position/title with responsibilities for AI | | | Chief information officer / Chief digital officer or equivalent | | | Chief AI officer | | | Chief analytics officer / Chief data officer / Head of data science or equivalent | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| | | MFT | 0 (0.0) | 16 (53.3) | 14 (46.7) | 2 (6.7) | 15 (50.0) | 13 (43.3) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 1 (3.3) | 17 (56.7) | 12 (40.0) | 0 (0.0) | 16 (53.3) | 14 (46.7) |
| | 250+ | ICT | 4 (13.3) | 16 (53.3) | 10 (33.3) | 3 (10.0) | 11 (36.7) | 16 (53.3) | 2 (6.7) | 4 (13.3) | 24 (80.0) | 1 (3.3) | 25 (83.3) | 4 (13.3) | 1 (3.3) | 11 (36.7) | 18 (60.0) |
| | | MFT | 1 (3.3) | 16 (53.3) | 13 (43.3) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 0 (0.0) | 7 (23.3) | 23 (76.7) | 0 (0.0) | 21 (70.0) | 9 (30.0) | 0 (0.0) | 9 (30.0) | 21 (70.0) |
| ITA | 50-249 | ICT | 0 (0.0) | 19 (63.3) | 11 (36.7) | 1 (3.3) | 20 (66.7) | 9 (30.0) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) |
| | | MFT | 0 (0.0) | 16 (53.3) | 14 (46.7) | 1 (3.3) | 18 (60.0) | 11 (36.7) | 1 (3.3) | 4 (13.3) | 25 (83.3) | 1 (3.3) | 20 (66.7) | 9 (30.0) | 1 (3.3) | 8 (26.7) | 21 (70.0) |
| | 250+ | ICT | 1 (3.3) | 13 (43.3) | 16 (53.3) | 3 (10.0) | 16 (53.3) | 11 (36.7) | 0 (0.0) | 8 (26.7) | 22 (73.3) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 8 (26.7) | 22 (73.3) |
| | | MFT | 3 (10.0) | 17 (56.7) | 10 (33.3) | 2 (6.7) | 16 (53.3) | 12 (40.0) | 3 (10.0) | 7 (23.3) | 20 (66.7) | 3 (10.0) | 17 (56.7) | 10 (33.3) | 2 (6.7) | 12 (40.0) | 16 (53.3) |
| JPN | 50-249 | ICT | 0 (0.0) | 18 (60.0) | 12 (40.0) | 3 (10.0) | 12 (40.0) | 15 (50.0) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 12 (40.0) | 18 (60.0) |
| | | MFT | 2 (6.7) | 8 (26.7) | 20 (66.7) | 4 (13.3) | 10 (33.3) | 16 (53.3) | 3 (10.0) | 4 (13.3) | 23 (76.7) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 3 (10.0) | 3 (10.0) | 24 (80.0) |
| | 250+ | ICT | 0 (0.0) | 18 (60.0) | 12 (40.0) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 0 (0.0) | 6 (20.0) | 24 (80.0) | 1 (3.3) | 21 (70.0) | 8 (26.7) | 0 (0.0) | 12 (40.0) | 18 (60.0) |
| | | MFT | 2 (6.7) | 11 (36.7) | 17 (56.7) | 2 (6.7) | 7 (23.3) | 21 (70.0) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 2 (6.7) | 10 (33.3) | 18 (60.0) |
| USA | 50-249 | ICT | 0 (0.0) | 22 (73.3) | 8 (26.7) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 26 (86.7) | 4 (13.3) | 0 (0.0) | 8 (26.7) | 22 (73.3) |
| | | MFT | 0 (0.0) | 19 (63.3) | 11 (36.7) | 2 (6.7) | 10 (33.3) | 18 (60.0) | 1 (3.3) | 6 (20.0) | 23 (76.7) | 1 (3.3) | 28 (93.3) | 1 (3.3) | 1 (3.3) | 13 (43.3) | 16 (53.3) |
| | 250+ | ICT | 1 (3.3) | 18 (60.0) | 11 (36.7) | 4 (13.3) | 15 (50.0) | 11 (36.7) | 1 (3.3) | 6 (20.0) | 23 (76.7) | 2 (6.7) | 24 (80.0) | 4 (13.3) | 2 (6.7) | 9 (30.0) | 19 (63.3) |
| | | MFT | 1 (3.3) | 14 (46.7) | 15 (50.0) | 4 (13.3) | 15 (50.0) | 11 (36.7) | 0 (0.0) | 3 (10.0) | 27 (90.0) | 2 (6.7) | 25 (83.3) | 3 (10.0) | 1 (3.3) | 13 (43.3) | 16 (53.3) |

Note: MFT = Manufacturing. Numbers presented in parentheses are percentages.

## Table E.7. Q6 - In the past 12 months, have any of the following conditions limited the use of cloud computing in your enterprise?

| Country | Enterprise size | Sector | High cost of retooling systems | | | Concerns about corporate compliance | | | Concerns about customisation of applications | | | Concerns about network stability | | | Lack of availability of adequate cloud computing services | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| CAN | 50-249 | ICT | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) |
| | | MFT | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 18 (60.0) | 12 (40.0) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 13 (43.3) | 17 (56.7) |
| | 250+ | ICT | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 25 (83.3) | 5 (16.7) |
| | | MFT | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 13 (43.3) | 17 (56.7) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 1 (3.3) | 20 (66.7) | 9 (30.0) |

| Country | Enterprise size | Sector | High cost of retooling systems | | | Concerns about corporate compliance | | | Concerns about customisation of applications | | | Concerns about network stability | | | Lack of availability of adequate cloud computing services | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| DEU | 50-249 | ICT | 0 (0.0) | 6 (20.0) | 24 (80.0) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 16 (53.3) | 14 (46.7) |
| | | MFT | 1 (3.3) | 9 (30.0) | 20 (66.7) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 9 (30.0) | 21 (70.0) | 1 (3.3) | 10 (33.3) | 19 (63.3) | 1 (3.3) | 20 (66.7) | 9 (30.0) |
| | 250+ | ICT | 0 (0.0) | 18 (60.0) | 12 (40.0) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 0 (0.0) | 21 (70.0) | 9 (30.0) | 0 (0.0) | 18 (60.0) | 12 (40.0) |
| | | MFT | 1 (3.3) | 16 (53.3) | 13 (43.3) | 1 (3.3) | 12 (40.0) | 17 (56.7) | 2 (6.7) | 15 (50.0) | 13 (43.3) | 1 (3.3) | 14 (46.7) | 15 (50.0) | 2 (6.7) | 22 (73.3) | 6 (20.0) |
| FRA | 50-249 | ICT | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 21 (70.0) | 9 (30.0) |
| | | MFT | 0 (0.0) | 5 (16.7) | 25 (83.3) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 13 (43.3) | 17 (56.7) |
| | 250+ | ICT | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 20 (66.7) | 10 (33.3) |
| | | MFT | 1 (3.3) | 15 (50.0) | 14 (46.7) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 2 (6.7) | 18 (60.0) | 10 (33.3) |
| GBR | 50-249 | ICT | 0 (0.0) | 6 (20.0) | 24 (80.0) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 18 (60.0) | 12 (40.0) |
| | | MFT | 0 (0.0) | 6 (20.0) | 24 (80.0) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 11 (36.7) | 19 (63.3) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 20 (66.7) | 10 (33.3) |
| | 250+ | ICT | 1 (3.3) | 18 (60.0) | 11 (36.7) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 0 (0.0) | 18 (60.0) | 12 (40.0) | 3 (10.0) | 20 (66.7) | 7 (23.3) | 1 (3.3) | 20 (66.7) | 9 (30.0) |
| | | MFT | 0 (0.0) | 13 (43.3) | 17 (56.7) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 0 (0.0) | 20 (66.7) | 10 (33.3) |
| ITA | 50-249 | ICT | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 1 (3.3) | 16 (53.3) | 13 (43.3) | 0 (0.0) | 16 (53.3) | 14 (46.7) |
| | | MFT | 0 (0.0) | 13 (43.3) | 17 (56.7) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 10 (33.3) | 20 (66.7) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 18 (60.0) | 12 (40.0) |
| | 250+ | ICT | 1 (3.3) | 19 (63.3) | 10 (33.3) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 0 (0.0) | 18 (60.0) | 12 (40.0) | 0 (0.0) | 19 (63.3) | 11 (36.7) |
| | | MFT | 1 (3.3) | 16 (53.3) | 13 (43.3) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 1 (3.3) | 17 (56.7) | 12 (40.0) | 0 (0.0) | 18 (60.0) | 12 (40.0) | 1 (3.3) | 21 (70.0) | 8 (26.7) |
| JPN | 50-249 | ICT | 0 (0.0) | 11 (36.7) | 19 (63.3) | 1 (3.3) | 15 (50.0) | 14 (46.7) | 0 (0.0) | 12 (40.0) | 18 (60.0) | 1 (3.3) | 10 (33.3) | 19 (63.3) | 0 (0.0) | 24 (80.0) | 6 (20.0) |
| | | MFT | 1 (3.3) | 9 (30.0) | 20 (66.7) | 1 (3.3) | 20 (66.7) | 9 (30.0) | 1 (3.3) | 9 (30.0) | 20 (66.7) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 1 (3.3) | 10 (33.3) | 19 (63.3) |
| | 250+ | ICT | 0 (0.0) | 16 (53.3) | 14 (46.7) | 1 (3.3) | 19 (63.3) | 10 (33.3) | 1 (3.3) | 12 (40.0) | 17 (56.7) | 2 (6.7) | 12 (40.0) | 16 (53.3) | 0 (0.0) | 18 (60.0) | 12 (40.0) |
| | | MFT | 1 (3.3) | 19 (63.3) | 10 (33.3) | 0 (0.0) | 17 (56.7) | 13 (43.3) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 20 (66.7) | 10 (33.3) | 0 (0.0) | 21 (70.0) | 9 (30.0) |
| USA | 50-249 | ICT | 1 (3.3) | 13 (43.3) | 16 (53.3) | 0 (0.0) | 19 (63.3) | 11 (36.7) | 0 (0.0) | 13 (43.3) | 17 (56.7) | 2 (6.7) | 19 (63.3) | 9 (30.0) | 0 (0.0) | 24 (80.0) | 6 (20.0) |
| | | MFT | 1 (3.3) | 9 (30.0) | 20 (66.7) | 0 (0.0) | 18 (60.0) | 12 (40.0) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 16 (53.3) | 14 (46.7) | 0 (0.0) | 19 (63.3) | 11 (36.7) |
| | 250+ | ICT | 1 (3.3) | 15 (50.0) | 14 (46.7) | 0 (0.0) | 14 (46.7) | 16 (53.3) | 0 (0.0) | 15 (50.0) | 15 (50.0) | 1 (3.3) | 23 (76.7) | 6 (20.0) | 1 (3.3) | 26 (86.7) | 3 (10.0) |
| | | MFT | 1 (3.3) | 18 (60.0) | 11 (36.7) | 0 (0.0) | 13 (43.3) | 17 (56.7) | 1 (3.3) | 15 (50.0) | 14 (46.7) | 1 (3.3) | 20 (66.7) | 9 (30.0) | 0 (0.0) | 25 (83.3) | 5 (16.7) |

Note: MFT = Manufacturing. Numbers presented in parentheses are percentages.

## Table E.8. Q6 - In the past 12 months, have any of the following conditions limited the use of cloud computing in your enterprise? (continued)

| Country | Enterprise size | Sector | Do not see the advantages of cloud computing | | | Lack of support from top management | | | Lack of IT skills | | | The enterprise uses cloud computing without difficulty | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| CAN | 50-249 | ICT | 0 (0.0%) | 27 (90.0%) | 3 (10.0%) | 0 (0.0%) | 24 (80.0%) | 6 (20.0%) | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 11 (36.7%) | 19 (63.3%) |
| | | MFT | 2 (6.7%) | 16 (53.3%) | 12 (40.0%) | 0 (0.0%) | 16 (53.3%) | 14 (46.7%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 11 (36.7%) | 19 (63.3%) |
| | 250+ | ICT | 0 (0.0%) | 26 (86.7%) | 4 (13.3%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 0 (0.0%) | 21 (70.0%) | 9 (30.0%) | 1 (3.3%) | 12 (40.0%) | 17 (56.7%) |
| | | MFT | 1 (3.3%) | 18 (60.0%) | 11 (36.7%) | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 17 (56.7%) | 13 (43.3%) | 0 (0.0%) | 12 (40.0%) | 18 (60.0%) |
| DEU | 50-249 | ICT | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 0 (0.0%) | 21 (70.0%) | 9 (30.0%) | 0 (0.0%) | 17 (56.7%) | 13 (43.3%) | 1 (3.3%) | 17 (56.7%) | 12 (40.0%) |
| | | MFT | 1 (3.3%) | 16 (53.3%) | 13 (43.3%) | 1 (3.3%) | 18 (60.0%) | 11 (36.7%) | 1 (3.3%) | 22 (73.3%) | 7 (23.3%) | 1 (3.3%) | 9 (30.0%) | 20 (66.7%) |
| | 250+ | ICT | 0 (0.0%) | 23 (76.7%) | 7 (23.3%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 12 (40.0%) | 18 (60.0%) |
| | | MFT | 2 (6.7%) | 24 (80.0%) | 4 (13.3%) | 2 (6.7%) | 20 (66.7%) | 8 (26.7%) | 2 (6.7%) | 20 (66.7%) | 8 (26.7%) | 3 (10.0%) | 13 (43.3%) | 14 (46.7%) |
| FRA | 50-249 | ICT | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 26 (86.7%) | 4 (13.3%) | 0 (0.0%) | 14 (46.7%) | 16 (53.3%) |
| | | MFT | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 15 (50.0%) | 15 (50.0%) | 0 (0.0%) | 13 (43.3%) | 17 (56.7%) | 0 (0.0%) | 6 (20.0%) | 24 (80.0%) |
| | 250+ | ICT | 0 (0.0%) | 25 (83.3%) | 5 (16.7%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 1 (3.3%) | 7 (23.3%) | 22 (73.3%) |
| | | MFT | 1 (3.3%) | 18 (60.0%) | 11 (36.7%) | 1 (3.3%) | 22 (73.3%) | 7 (23.3%) | 0 (0.0%) | 15 (50.0%) | 15 (50.0%) | 0 (0.0%) | 11 (36.7%) | 19 (63.3%) |
| GBR | 50-249 | ICT | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 16 (53.3%) | 14 (46.7%) | 0 (0.0%) | 10 (33.3%) | 20 (66.7%) |
| | | MFT | 1 (3.3%) | 21 (70.0%) | 8 (26.7%) | 0 (0.0%) | 16 (53.3%) | 14 (46.7%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 1 (3.3%) | 25 (83.3%) | 4 (13.3%) | 1 (3.3%) | 23 (76.7%) | 6 (20.0%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 12 (40.0%) | 18 (60.0%) |
| | | MFT | 0 (0.0%) | 25 (83.3%) | 5 (16.7%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 15 (50.0%) | 15 (50.0%) |
| ITA | 50-249 | ICT | 0 (0.0%) | 21 (70.0%) | 9 (30.0%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) |
| | | MFT | 0 (0.0%) | 21 (70.0%) | 9 (30.0%) | 0 (0.0%) | 23 (76.7%) | 7 (23.3%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 1 (3.3%) | 14 (46.7%) | 15 (50.0%) |
| | 250+ | ICT | 0 (0.0%) | 28 (93.3%) | 2 (6.7%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 0 (0.0%) | 8 (26.7%) | 22 (73.3%) |
| | | MFT | 2 (6.7%) | 21 (70.0%) | 7 (23.3%) | 1 (3.3%) | 21 (70.0%) | 8 (26.7%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 2 (6.7%) | 11 (36.7%) | 17 (56.7%) |
| JPN | 50-249 | ICT | 0 (0.0%) | 23 (76.7%) | 7 (23.3%) | 0 (0.0%) | 24 (80.0%) | 6 (20.0%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 10 (33.3%) | 20 (66.7%) |
| | | MFT | 1 (3.3%) | 16 (53.3%) | 13 (43.3%) | 0 (0.0%) | 19 (63.3%) | 11 (36.7%) | 0 (0.0%) | 13 (43.3%) | 17 (56.7%) | 2 (6.7%) | 17 (56.7%) | 11 (36.7%) |
| | 250+ | ICT | 1 (3.3%) | 23 (76.7%) | 6 (20.0%) | 0 (0.0%) | 24 (80.0%) | 6 (20.0%) | 0 (0.0%) | 25 (83.3%) | 5 (16.7%) | 0 (0.0%) | 5 (16.7%) | 25 (83.3%) |
| | | MFT | 0 (0.0%) | 24 (80.0%) | 6 (20.0%) | 0 (0.0%) | 23 (76.7%) | 7 (23.3%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 16 (53.3%) | 14 (46.7%) |

| Country | Enterprise size | Sector | Do not see the advantages of cloud computing | | | Lack of support from top management | | | Lack of IT skills | | | The enterprise uses cloud computing without difficulty | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes | Don't know | No | Yes |
| USA | 50-249 | ICT | 0 (0.0%) | 29 (96.7%) | 1 (3.3%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 22 (73.3%) | 8 (26.7%) | 0 (0.0%) | 10 (33.3%) | 20 (66.7%) |
| | | MFT | 0 (0.0%) | 26 (86.7%) | 4 (13.3%) | 0 (0.0%) | 23 (76.7%) | 7 (23.3%) | 0 (0.0%) | 20 (66.7%) | 10 (33.3%) | 0 (0.0%) | 12 (40.0%) | 18 (60.0%) |
| | 250+ | ICT | 0 (0.0%) | 29 (96.7%) | 1 (3.3%) | 1 (3.3%) | 23 (76.7%) | 6 (20.0%) | 0 (0.0%) | 18 (60.0%) | 12 (40.0%) | 0 (0.0%) | 14 (46.7%) | 16 (53.3%) |
| | | MFT | 1 (3.3%) | 24 (80.0%) | 5 (16.7%) | 0 (0.0%) | 24 (80.0%) | 6 (20.0%) | 0 (0.0%) | 21 (70.0%) | 9 (30.0%) | 0 (0.0%) | 13 (43.3%) | 17 (56.7%) |

Note: MFT = Manufacturing.

## Table E.9. Q7 - In the past 12 months, has your enterprise implemented any of the following practices to develop artificial intelligence?

| Country | Enterprise size | Sector | Training of employees | | Hiring new staff | | R&D on AI to use by the enterprise | | Purchase of off-the-shelf software or hardware or through business advisory services such as consultancy | | Use of customised systems built by third parties | | Created a senior management role or a team with responsibilities for AI | | Partnership with a national or international enterprise with capacities in AI | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| CAN | 50-249 | ICT | 8 (26.7) | 22 (73.3) | 10 (33.3) | 20 (66.7) | 8 (26.7) | 22 (73.3) | 15 (50.0) | 15 (50.0) | 11 (36.7) | 19 (63.3) | 16 (53.3) | 14 (46.7) | 21 (70.0) | 9 (30.0) |
| | | MFT | 9 (30.0) | 21 (70.0) | 10 (33.3) | 20 (66.7) | 12 (40.0) | 18 (60.0) | 13 (43.3) | 17 (56.7) | 7 (23.3) | 23 (76.7) | 9 (30.0) | 21 (70.0) | 12 (40.0) | 18 (60.0) |
| | 250+ | ICT | 9 (30.0) | 21 (70.0) | 9 (30.0) | 21 (70.0) | 9 (30.0) | 21 (70.0) | 14 (46.7) | 16 (53.3) | 8 (26.7) | 22 (73.3) | 20 (66.7) | 10 (33.3) | 16 (53.3) | 14 (46.7) |
| | | MFT | 10 (33.3) | 20 (66.7) | 19 (63.3) | 11 (36.7) | 4 (13.3) | 26 (86.7) | 11 (36.7) | 19 (63.3) | 14 (46.7) | 16 (53.3) | 18 (60.0) | 12 (40.0) | 15 (50.0) | 15 (50.0) |
| DEU | 50-249 | ICT | 6 (20.0) | 24 (80.0) | 16 (53.3) | 14 (46.7) | 5 (16.7) | 25 (83.3) | 16 (53.3) | 14 (46.7) | 18 (60.0) | 12 (40.0) | 13 (43.3) | 17 (56.7) | 20 (66.7) | 10 (33.3) |
| | | MFT | 10 (33.3) | 20 (66.7) | 17 (56.7) | 13 (43.3) | 8 (26.7) | 22 (73.3) | 14 (46.7) | 16 (53.3) | 15 (50.0) | 15 (50.0) | 12 (40.0) | 18 (60.0) | 14 (46.7) | 16 (53.3) |
| | 250+ | ICT | 4 (13.3) | 26 (86.7) | 10 (33.3) | 20 (66.7) | 9 (30.0) | 21 (70.0) | 19 (63.3) | 11 (36.7) | 14 (46.7) | 16 (53.3) | 15 (50.0) | 15 (50.0) | 16 (53.3) | 14 (46.7) |
| | | MFT | 11 (36.7) | 19 (63.3) | 14 (46.7) | 16 (53.3) | 8 (26.7) | 22 (73.3) | 9 (30.0) | 21 (70.0) | 15 (50.0) | 15 (50.0) | 15 (50.0) | 15 (50.0) | 12 (40.0) | 18 (60.0) |
| FRA | 50-249 | ICT | 8 (26.7) | 22 (73.3) | 11 (36.7) | 19 (63.3) | 8 (26.7) | 22 (73.3) | 9 (30.0) | 21 (70.0) | 11 (36.7) | 19 (63.3) | 16 (53.3) | 14 (46.7) | 15 (50.0) | 15 (50.0) |
| | | MFT | 2 (6.7) | 28 (93.3) | 6 (20.0) | 24 (80.0) | 14 (46.7) | 16 (53.3) | 9 (30.0) | 21 (70.0) | 11 (36.7) | 19 (63.3) | 10 (33.3) | 20 (66.7) | 11 (36.7) | 19 (63.3) |
| | 250+ | ICT | 7 (23.3) | 23 (76.7) | 9 (30.0) | 21 (70.0) | 5 (16.7) | 25 (83.3) | 14 (46.7) | 16 (53.3) | 15 (50.0) | 15 (50.0) | 16 (53.3) | 14 (46.7) | 12 (40.0) | 18 (60.0) |
| | | MFT | 6 (20.0) | 24 (80.0) | 5 (16.7) | 25 (83.3) | 10 (33.3) | 20 (66.7) | 8 (26.7) | 22 (73.3) | 10 (33.3) | 20 (66.7) | 11 (36.7) | 19 (63.3) | 11 (36.7) | 19 (63.3) |
| GBR | 50-249 | ICT | 9 (30.0) | 21 (70.0) | 18 (60.0) | 12 (40.0) | 12 (40.0) | 18 (60.0) | 13 (43.3) | 17 (56.7) | 7 (23.3) | 23 (76.7) | 19 (63.3) | 11 (36.7) | 19 (63.3) | 11 (36.7) |
| | | MFT | 6 | 24 | 15 | 15 | 10 | 20 | 8 | 22 | 8 | 22 | 12 | 18 | 18 | 12 |

| Country | Enterprise size | Sector | Training of employees | | Hiring new staff | | R&D on AI to use by the enterprise | | Purchase of off-the-shelf software or hardware or through business advisory services such as consultancy | | Use of customised systems built by third parties | | Created a senior management role or a team with responsibilities for AI | | Partnership with a national or international enterprise with capacities in AI | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| | | | (20.0) | (80.0) | (50.0) | (50.0) | (33.3) | (66.7) | (26.7) | (73.3) | (26.7) | (73.3) | (40.0) | (60.0) | (60.0) | (40.0) |
| | 250+ | ICT | 10 (34.5) | 19 (65.5) | 5 (17.2) | 24 (82.8) | 7 (24.1) | 22 (75.9) | 12 (41.4) | 17 (58.6) | 14 (48.3) | 15 (51.7) | 9 (31.0) | 20 (69.0) | 15 (51.7) | 14 (48.3) |
| | | MFT | 5 (16.7) | 25 (83.3) | 7 (23.3) | 23 (76.7) | 7 (23.3) | 23 (76.7) | 13 (43.3) | 17 (56.7) | 12 (40.0) | 18 (60.0) | 12 (40.0) | 18 (60.0) | 16 (53.3) | 14 (46.7) |
| ITA | 50-249 | ICT | 9 (30.0) | 21 (70.0) | 14 (46.7) | 16 (53.3) | 7 (23.3) | 23 (76.7) | 16 (53.3) | 14 (46.7) | 14 (46.7) | 16 (53.3) | 17 (56.7) | 13 (43.3) | 17 (56.7) | 13 (43.3) |
| | | MFT | 8 (26.7) | 22 (73.3) | 15 (50.0) | 15 (50.0) | 10 (33.3) | 20 (66.7) | 18 (60.0) | 12 (40.0) | 10 (33.3) | 20 (66.7) | 16 (53.3) | 14 (46.7) | 16 (53.3) | 14 (46.7) |
| | 250+ | ICT | 9 (30.0) | 21 (70.0) | 13 (43.3) | 17 (56.7) | 8 (26.7) | 22 (73.3) | 16 (53.3) | 14 (46.7) | 11 (36.7) | 19 (63.3) | 16 (53.3) | 14 (46.7) | 22 (73.3) | 8 (26.7) |
| | | MFT | 6 (20.0) | 24 (80.0) | 13 (43.3) | 17 (56.7) | 12 (40.0) | 18 (60.0) | 10 (33.3) | 20 (66.7) | 17 (56.7) | 13 (43.3) | 18 (60.0) | 12 (40.0) | 14 (46.7) | 16 (53.3) |
| JPN | 50-249 | ICT | 6 (20.0) | 24 (80.0) | 16 (53.3) | 14 (46.7) | 10 (33.3) | 20 (66.7) | 8 (26.7) | 22 (73.3) | 11 (36.7) | 19 (63.3) | 17 (56.7) | 13 (43.3) | 16 (53.3) | 14 (46.7) |
| | | MFT | 8 (26.7) | 22 (73.3) | 8 (26.7) | 22 (73.3) | 6 (20.0) | 24 (80.0) | 6 (20.0) | 24 (80.0) | 9 (30.0) | 21 (70.0) | 10 (33.3) | 20 (66.7) | 12 (40.0) | 18 (60.0) |
| | 250+ | ICT | 4 (13.3) | 26 (86.7) | 6 (20.0) | 24 (80.0) | 13 (43.3) | 17 (56.7) | 16 (53.3) | 14 (46.7) | 14 (46.7) | 16 (53.3) | 16 (53.3) | 14 (46.7) | 15 (50.0) | 15 (50.0) |
| | | MFT | 17 (56.7) | 13 (43.3) | 12 (40.0) | 18 (60.0) | 7 (23.3) | 23 (76.7) | 8 (26.7) | 22 (73.3) | 9 (30.0) | 21 (70.0) | 12 (40.0) | 18 (60.0) | 12 (40.0) | 18 (60.0) |
| USA | 50-249 | ICT | 11 (36.7) | 19 (63.3) | 8 (26.7) | 22 (73.3) | 5 (16.7) | 25 (83.3) | 16 (53.3) | 14 (46.7) | 17 (56.7) | 13 (43.3) | 16 (53.3) | 14 (46.7) | 21 (70.0) | 9 (30.0) |
| | | MFT | 12 (40.0) | 18 (60.0) | 18 (60.0) | 12 (40.0) | 5 (16.7) | 25 (83.3) | 10 (33.3) | 20 (66.7) | 15 (50.0) | 15 (50.0) | 20 (66.7) | 10 (33.3) | 20 (66.7) | 10 (33.3) |
| | 250+ | ICT | 2 (6.7) | 28 (93.3) | 4 (13.3) | 26 (86.7) | 4 (13.3) | 26 (86.7) | 14 (46.7) | 16 (53.3) | 17 (56.7) | 13 (43.3) | 18 (60.0) | 12 (40.0) | 21 (70.0) | 9 (30.0) |
| | | MFT | 8 (26.7) | 22 (73.3) | 5 (16.7) | 25 (83.3) | 3 (10.0) | 27 (90.0) | 13 (43.3) | 17 (56.7) | 12 (40.0) | 18 (60.0) | 21 (70.0) | 9 (30.0) | 21 (70.0) | 9 (30.0) |

Note: MFT = Manufacturing. Numbers presented in parentheses are percentages.

## Table E.10. Q8 - Services that provide access to information or advice

| Country | Enterprise size | Sector | Services that provide access to information or advice | | Training services | | Services that promote access to finance, such as subsidies or credit guarantees | |
|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes |
| CAN | 50-249 | ICT | 8 (26.7%) | 22 (73.3%) | 10 (33.3%) | 20 (66.7%) | 16 (53.3%) | 14 (46.7%) |
| | | Manufacturing | 2 (6.7%) | 28 (93.3%) | 9 (30.0%) | 21 (70.0%) | 14 (46.7%) | 16 (53.3%) |
| | 250+ | ICT | 12 (41.4%) | 17 (58.6%) | 13 (44.8%) | 16 (55.2%) | 16 (55.2%) | 13 (44.8%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 15 (50.0%) | 15 (50.0%) | 18 (60.0%) | 12 (40.0%) |
| DEU | 50-249 | ICT | 10 (33.3%) | 20 (66.7%) | 14 (46.7%) | 16 (53.3%) | 14 (46.7%) | 16 (53.3%) |
| | | Manufacturing | 6 (20.0%) | 24 (80.0%) | 12 (40.0%) | 18 (60.0%) | 13 (43.3%) | 17 (56.7%) |
| | 250+ | ICT | 11 (36.7%) | 19 (63.3%) | 13 (43.3%) | 17 (56.7%) | 17 (56.7%) | 13 (43.3%) |
| | | Manufacturing | 14 (46.7%) | 16 (53.3%) | 16 (53.3%) | 14 (46.7%) | 23 (76.7%) | 7 (23.3%) |

| Country | Enterprise size | Sector | Services that provide access to information or advice | | Training services | | Services that promote access to finance, such as subsidies or credit guarantees | |
|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes |
| FRA | 50-249 | ICT | 8 (26.7%) | 22 (73.3%) | 7 (23.3%) | 23 (76.7%) | 15 (50.0%) | 15 (50.0%) |
| | | Manufacturing | 2 (6.7%) | 28 (93.3%) | 8 (26.7%) | 22 (73.3%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 10 (33.3%) | 20 (66.7%) | 16 (53.3%) | 14 (46.7%) | 17 (56.7%) | 13 (43.3%) |
| | | Manufacturing | 10 (33.3%) | 20 (66.7%) | 13 (43.3%) | 17 (56.7%) | 19 (63.3%) | 11 (36.7%) |
| GBR | 50-249 | ICT | 9 (30.0%) | 21 (70.0%) | 9 (30.0%) | 21 (70.0%) | 19 (63.3%) | 11 (36.7%) |
| | | Manufacturing | 4 (13.3%) | 26 (86.7%) | 10 (33.3%) | 20 (66.7%) | 13 (43.3%) | 17 (56.7%) |
| | 250+ | ICT | 10 (35.7%) | 18 (64.3%) | 17 (60.7%) | 11 (39.3%) | 21 (75.0%) | 7 (25.0%) |
| | | Manufacturing | 7 (24.1%) | 22 (75.9%) | 18 (62.1%) | 11 (37.9%) | 21 (72.4%) | 8 (27.6%) |
| ITA | 50-249 | ICT | 8 (26.7%) | 22 (73.3%) | 13 (43.3%) | 17 (56.7%) | 20 (66.7%) | 10 (33.3%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 8 (26.7%) | 22 (73.3%) | 12 (40.0%) | 18 (60.0%) |
| | 250+ | ICT | 5 (17.2%) | 24 (82.8%) | 12 (41.4%) | 17 (58.6%) | 17 (58.6%) | 12 (41.4%) |
| | | Manufacturing | 11 (36.7%) | 19 (63.3%) | 15 (50.0%) | 15 (50.0%) | 16 (53.3%) | 14 (46.7%) |
| JPN | 50-249 | ICT | 6 (20.7%) | 23 (79.3%) | 8 (27.6%) | 21 (72.4%) | 14 (48.3%) | 15 (51.7%) |
| | | Manufacturing | 4 (13.3%) | 26 (86.7%) | 10 (33.3%) | 20 (66.7%) | 12 (40.0%) | 18 (60.0%) |
| | 250+ | ICT | 3 (10.0%) | 27 (90.0%) | 9 (30.0%) | 21 (70.0%) | 17 (56.7%) | 13 (43.3%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 17 (56.7%) | 13 (43.3%) | 16 (53.3%) | 14 (46.7%) |
| USA | 50-249 | ICT | 16 (53.3%) | 14 (46.7%) | 18 (60.0%) | 12 (40.0%) | 24 (80.0%) | 6 (20.0%) |
| | | Manufacturing | 6 (20.0%) | 24 (80.0%) | 11 (36.7%) | 19 (63.3%) | 24 (80.0%) | 6 (20.0%) |
| | 250+ | ICT | 14 (46.7%) | 16 (53.3%) | 16 (53.3%) | 14 (46.7%) | 24 (80.0%) | 6 (20.0%) |
| | | Manufacturing | 16 (53.3%) | 14 (46.7%) | 18 (60.0%) | 12 (40.0%) | 25 (83.3%) | 5 (16.7%) |

## Table E.11. Q9 - In the past 12 months, has your enterprise established collaborations to develop artificial intelligence …

| Country | Enterprise size | Sector | With university faculty members, PhD or postdoctoral students? | | With undergraduate students? | | With researchers in public research organisations? | | With other partners? | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes |
| CAN | 50-249 | ICT | 12 (40.0%) | 18 (60.0%) | 19 (63.3%) | 11 (36.7%) | 19 (63.3%) | 11 (36.7%) | 13 (43.3%) | 17 (56.7%) |
| | | MFT | 9 (30.0%) | 21 (70.0%) | 15 (50.0%) | 15 (50.0%) | 8 (26.7%) | 22 (73.3%) | 16 (53.3%) | 14 (46.7%) |
| | 250+ | ICT | 19 (63.3%) | 11 (36.7%) | 23 (76.7%) | 7 (23.3%) | 15 (50.0%) | 15 (50.0%) | 14 (46.7%) | 16 (53.3%) |
| | | MFT | 19 (63.3%) | 11 (36.7%) | 22 (73.3%) | 8 (26.7%) | 16 (53.3%) | 14 (46.7%) | 21 (70.0%) | 9 (30.0%) |
| DEU | 50-249 | ICT | 13 (43.3%) | 17 (56.7%) | 23 (76.7%) | 7 (23.3%) | 15 (50.0%) | 15 (50.0%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 13 (43.3%) | 17 (56.7%) | 21 (70.0%) | 9 (30.0%) | 14 (46.7%) | 16 (53.3%) | 16 (53.3%) | 14 (46.7%) |
| | 250+ | ICT | 6 (20.0%) | 24 (80.0%) | 19 (63.3%) | 11 (36.7%) | 16 (53.3%) | 14 (46.7%) | 13 (43.3%) | 17 (56.7%) |
| | | MFT | 6 (20.0%) | 24 (80.0%) | 17 (56.7%) | 13 (43.3%) | 17 (56.7%) | 13 (43.3%) | 16 (53.3%) | 14 (46.7%) |
| FRA | 50-249 | ICT | 14 (46.7%) | 16 (53.3%) | 18 (60.0%) | 12 (40.0%) | 14 (46.7%) | 16 (53.3%) | 16 (53.3%) | 14 (46.7%) |
| | | MFT | 4 (13.3%) | 26 (86.7%) | 10 (33.3%) | 20 (66.7%) | 11 (36.7%) | 19 (63.3%) | 8 (26.7%) | 22 (73.3%) |
| | 250+ | ICT | 9 (30.0%) | 21 (70.0%) | 20 (66.7%) | 10 (33.3%) | 18 (60.0%) | 12 (40.0%) | 7 (23.3%) | 23 (76.7%) |

| Country | Enterprise size | Sector | With university faculty members, PhD or postdoctoral students? | | With undergraduate students? | | With researchers in public research organisations? | | With other partners? | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes |
| | | MFT | 7 (23.3%) | 23 (76.7%) | 20 (66.7%) | 10 (33.3%) | 15 (50.0%) | 15 (50.0%) | 9 (30.0%) | 21 (70.0%) |
| GBR | 50-249 | ICT | 18 (60.0%) | 12 (40.0%) | 20 (66.7%) | 10 (33.3%) | 12 (40.0%) | 18 (60.0%) | 16 (53.3%) | 14 (46.7%) |
| | | MFT | 13 (43.3%) | 17 (56.7%) | 16 (53.3%) | 14 (46.7%) | 13 (43.3%) | 17 (56.7%) | 11 (36.7%) | 19 (63.3%) |
| | 250+ | ICT | 16 (53.3%) | 14 (46.7%) | 19 (63.3%) | 11 (36.7%) | 16 (53.3%) | 14 (46.7%) | 8 (26.7%) | 22 (73.3%) |
| | | MFT | 15 (50.0%) | 15 (50.0%) | 20 (66.7%) | 10 (33.3%) | 14 (46.7%) | 16 (53.3%) | 12 (40.0%) | 18 (60.0%) |
| ITA | 50-249 | ICT | 13 (43.3%) | 17 (56.7%) | 20 (66.7%) | 10 (33.3%) | 11 (36.7%) | 19 (63.3%) | 18 (60.0%) | 12 (40.0%) |
| | | MFT | 16 (53.3%) | 14 (46.7%) | 20 (66.7%) | 10 (33.3%) | 9 (30.0%) | 21 (70.0%) | 13 (43.3%) | 17 (56.7%) |
| | 250+ | ICT | 12 (40.0%) | 18 (60.0%) | 23 (76.7%) | 7 (23.3%) | 13 (43.3%) | 17 (56.7%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 12 (40.0%) | 18 (60.0%) | 19 (63.3%) | 11 (36.7%) | 18 (60.0%) | 12 (40.0%) | 15 (50.0%) | 15 (50.0%) |
| JPN | 50-249 | ICT | 18 (60.0%) | 12 (40.0%) | 22 (73.3%) | 8 (26.7%) | 16 (53.3%) | 14 (46.7%) | 13 (43.3%) | 17 (56.7%) |
| | | MFT | 11 (36.7%) | 19 (63.3%) | 14 (46.7%) | 16 (53.3%) | 5 (16.7%) | 25 (83.3%) | 9 (30.0%) | 21 (70.0%) |
| | 250+ | ICT | 12 (40.0%) | 18 (60.0%) | 24 (80.0%) | 6 (20.0%) | 15 (50.0%) | 15 (50.0%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 15 (50.0%) | 15 (50.0%) | 28 (93.3%) | 2 (6.7%) | 14 (46.7%) | 16 (53.3%) | 12 (40.0%) | 18 (60.0%) |
| USA | 50-249 | ICT | 13 (43.3%) | 17 (56.7%) | 21 (70.0%) | 9 (30.0%) | 19 (63.3%) | 11 (36.7%) | 15 (50.0%) | 15 (50.0%) |
| | | MFT | 19 (65.5%) | 10 (34.5%) | 25 (86.2%) | 4 (13.8%) | 16 (55.2%) | 13 (44.8%) | 6 (20.7%) | 23 (79.3%) |
| | 250+ | ICT | 19 (63.3%) | 11 (36.7%) | 21 (70.0%) | 9 (30.0%) | 19 (63.3%) | 11 (36.7%) | 14 (46.7%) | 16 (53.3%) |
| | | MFT | 18 (60.0%) | 12 (40.0%) | 22 (73.3%) | 8 (26.7%) | 17 (56.7%) | 13 (43.3%) | 13 (43.3%) | 17 (56.7%) |

Note: MFT = Manufacturing.

## Table E.12. Q10 - In the past 12 months, have any of the following obstacles limited your enterprise in implementing artificial intelligence applications?

| Country | Enterprise size | Sector | Difficulties in estimating the returns on investment in AI applications | | Concerns related to data privacy, data protection or data security | | Scarcity of cloud computing solutions that guarantee data security and regulatory compliance | | Lack of clarity about the legal consequences in case of damage caused by the use of AI | | Lack of vendors of AI systems offering solutions tailored to your enterprise's needs | | Lack of external finance for investment to support AI adoption | | Reluctance of staff to adopt AI | | Difficulties to retrain or upskill staff | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| CAN | 50-249 | ICT | 13 (43.3) | 17 (56.7) | 8 (26.7) | 22 (73.3) | 18 (60.0) | 12 (40.0) | 20 (66.7) | 10 (33.3) | 18 (60.0) | 12 (40.0) | 18 (60.0) | 12 (40.0) | 19 (63.3) | 11 (36.7) | 15 (50.0) | 15 (50.0) |
| | | MFT | 10 (33.3) | 20 (66.7) | 10 (33.3) | 20 (66.7) | 13 (43.3) | 17 (56.7) | 14 (46.7) | 16 (53.3) | 13 (43.3) | 17 (56.7) | 10 (33.3) | 20 (66.7) | 19 (63.3) | 11 (36.7) | 10 (33.3) | 20 (66.7) |

| Country | Enterprise size | Sector | Difficulties in estimating the returns on investment in AI applications | | Concerns related to data privacy, data protection or data security | | Scarcity of cloud computing solutions that guarantee data security and regulatory compliance | | Lack of clarity about the legal consequences in case of damage caused by the use of AI | | Lack of vendors of AI systems offering solutions tailored to your enterprise's needs | | Lack of external finance for investment to support AI adoption | | Reluctance of staff to adopt AI | | Difficulties to retrain or upskill staff | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| | 250+ | ICT | 15 (50.0) | 15 (50.0) | 10 (33.3) | 20 (66.7) | 16 (53.3) | 14 (46.7) | 18 (60.0) | 12 (40.0) | 20 (66.7) | 10 (33.3) | 19 (63.3) | 11 (36.7) | 19 (63.3) | 11 (36.7) | 14 (46.7) | 16 (53.3) |
| | | MFT | 14 (46.7) | 16 (53.3) | 16 (53.3) | 14 (46.7) | 15 (50.0) | 15 (50.0) | 17 (56.7) | 13 (43.3) | 17 (56.7) | 13 (43.3) | 19 (63.3) | 11 (36.7) | 13 (43.3) | 17 (56.7) | 12 (40.0) | 18 (60.0) |
| DEU | 50-249 | ICT | 12 (40.0) | 18 (60.0) | 17 (56.7) | 13 (43.3) | 14 (46.7) | 16 (53.3) | 20 (66.7) | 10 (33.3) | 12 (40.0) | 18 (60.0) | 17 (56.7) | 13 (43.3) | 21 (70.0) | 9 (30.0) | 20 (66.7) | 10 (33.3) |
| | | MFT | 8 (26.7) | 22 (73.3) | 13 (43.3) | 17 (56.7) | 20 (66.7) | 10 (33.3) | 12 (40.0) | 18 (60.0) | 19 (63.3) | 11 (36.7) | 14 (46.7) | 16 (53.3) | 19 (63.3) | 11 (36.7) | 8 (26.7) | 22 (73.3) |
| | 250+ | ICT | 16 (53.3) | 14 (46.7) | 13 (43.3) | 17 (56.7) | 18 (60.0) | 12 (40.0) | 16 (53.3) | 14 (46.7) | 20 (66.7) | 10 (33.3) | 20 (66.7) | 10 (33.3) | 14 (46.7) | 16 (53.3) | 16 (53.3) | 14 (46.7) |
| | | MFT | 11 (36.7) | 19 (63.3) | 11 (36.7) | 19 (63.3) | 22 (73.3) | 8 (26.7) | 16 (53.3) | 14 (46.7) | 15 (50.0) | 15 (50.0) | 24 (80.0) | 6 (20.0) | 12 (40.0) | 18 (60.0) | 15 (50.0) | 15 (50.0) |
| FRA | 50-249 | ICT | 17 (56.7) | 13 (43.3) | 14 (46.7) | 16 (53.3) | 16 (53.3) | 14 (46.7) | 18 (60.0) | 12 (40.0) | 19 (63.3) | 11 (36.7) | 20 (66.7) | 10 (33.3) | 22 (73.3) | 8 (26.7) | 15 (50.0) | 15 (50.0) |
| | | MFT | 5 (16.7) | 25 (83.3) | 10 (33.3) | 20 (66.7) | 19 (63.3) | 11 (36.7) | 16 (53.3) | 14 (46.7) | 12 (40.0) | 18 (60.0) | 12 (40.0) | 18 (60.0) | 17 (56.7) | 13 (43.3) | 13 (43.3) | 17 (56.7) |
| | 250+ | ICT | 18 (60.0) | 12 (40.0) | 11 (36.7) | 19 (63.3) | 14 (46.7) | 16 (53.3) | 20 (66.7) | 10 (33.3) | 20 (66.7) | 10 (33.3) | 21 (70.0) | 9 (30.0) | 21 (70.0) | 9 (30.0) | 13 (43.3) | 17 (56.7) |
| | | MFT | 8 (27.6) | 21 (72.4) | 11 (37.9) | 18 (62.1) | 10 (34.5) | 19 (65.5) | 14 (48.3) | 15 (51.7) | 15 (51.7) | 14 (48.3) | 15 (51.7) | 14 (48.3) | 13 (44.8) | 16 (55.2) | 12 (41.4) | 17 (58.6) |
| GBR | 50-249 | ICT | 9 (30.0) | 21 (70.0) | 11 (36.7) | 19 (63.3) | 18 (60.0) | 12 (40.0) | 23 (76.7) | 7 (23.3) | 17 (56.7) | 13 (43.3) | 13 (43.3) | 17 (56.7) | 15 (50.0) | 15 (50.0) | 14 (46.7) | 16 (53.3) |
| | | MFT | 9 (30.0) | 21 (70.0) | 14 (46.7) | 16 (53.3) | 20 (66.7) | 10 (33.3) | 19 (63.3) | 11 (36.7) | 17 (56.7) | 13 (43.3) | 19 (63.3) | 11 (36.7) | 9 (30.0) | 21 (70.0) | 17 (56.7) | 13 (43.3) |
| | 250+ | ICT | 16 (53.3) | 14 (46.7) | 12 (40.0) | 18 (60.0) | 23 (76.7) | 7 (23.3) | 12 (40.0) | 18 (60.0) | 20 (66.7) | 10 (33.3) | 23 (76.7) | 7 (23.3) | 20 (66.7) | 10 (33.3) | 11 (36.7) | 19 (63.3) |
| | | MFT | 15 (50.0) | 15 (50.0) | 16 (53.3) | 14 (46.7) | 20 (66.7) | 10 (33.3) | 19 (63.3) | 11 (36.7) | 14 (46.7) | 16 (53.3) | 17 (56.7) | 13 (43.3) | 23 (76.7) | 7 (23.3) | 13 (43.3) | 17 (56.7) |
| ITA | 50-249 | ICT | 11 (37.9) | 18 (62.1) | 16 (55.2) | 13 (44.8) | 15 (51.7) | 14 (48.3) | 20 (69.0) | 9 (31.0) | 14 (48.3) | 15 (51.7) | 12 (41.4) | 17 (58.6) | 20 (69.0) | 9 (31.0) | 17 (58.6) | 12 (41.4) |
| | | MFT | 16 (53.3) | 14 (46.7) | 14 (46.7) | 16 (53.3) | 15 (50.0) | 15 (50.0) | 19 (63.3) | 11 (36.7) | 19 (63.3) | 11 (36.7) | 18 (60.0) | 12 (40.0) | 17 (56.7) | 13 (43.3) | 19 (63.3) | 11 (36.7) |
| | 250+ | ICT | 12 (40.0) | 18 (60.0) | 18 (60.0) | 12 (40.0) | 13 (43.3) | 17 (56.7) | 15 (50.0) | 15 (50.0) | 21 (70.0) | 9 (30.0) | 21 (70.0) | 9 (30.0) | 20 (66.7) | 10 (33.3) | 17 (56.7) | 13 (43.3) |
| | | MFT | 14 (48.3) | 15 (51.7) | 21 (72.4) | 8 (27.6) | 21 (72.4) | 8 (27.6) | 15 (51.7) | 14 (48.3) | 19 (65.5) | 10 (34.5) | 20 (69.0) | 9 (31.0) | 18 (62.1) | 11 (37.9) | 16 (55.2) | 13 (44.8) |
| JPN | 50-249 | ICT | 15 (50.0) | 15 (50.0) | 11 (36.7) | 19 (63.3) | 19 (63.3) | 11 (36.7) | 18 (60.0) | 12 (40.0) | 14 (46.7) | 16 (53.3) | 19 (63.3) | 11 (36.7) | 23 (76.7) | 7 (23.3) | 17 (56.7) | 13 (43.3) |
| | | MFT | 14 (46.7) | 16 (53.3) | 10 (33.3) | 20 (66.7) | 7 (23.3) | 23 (76.7) | 13 (43.3) | 17 (56.7) | 10 (33.3) | 20 (66.7) | 13 (43.3) | 17 (56.7) | 14 (46.7) | 16 (53.3) | 12 (40.0) | 18 (60.0) |
| | 250+ | ICT | 8 (26.7) | 22 (73.3) | 14 (46.7) | 16 (53.3) | 20 (66.7) | 10 (33.3) | 14 (46.7) | 16 (53.3) | 9 (30.0) | 21 (70.0) | 19 (63.3) | 11 (36.7) | 19 (63.3) | 11 (36.7) | 16 (53.3) | 14 (46.7) |
| | | MFT | 15 (50.0) | 15 (50.0) | 17 (56.7) | 13 (43.3) | 15 (50.0) | 15 (50.0) | 17 (56.7) | 13 (43.3) | 17 (56.7) | 13 (43.3) | 18 (60.0) | 12 (40.0) | 19 (63.3) | 11 (36.7) | 11 (36.7) | 19 (63.3) |
| USA | 50-249 | ICT | 11 (36.7) | 19 (63.3) | 15 (50.0) | 15 (50.0) | 23 (76.7) | 7 (23.3) | 21 (70.0) | 9 (30.0) | 22 (73.3) | 8 (26.7) | 19 (63.3) | 11 (36.7) | 23 (76.7) | 7 (23.3) | 15 (50.0) | 15 (50.0) |
| | | MFT | 10 (34.5) | 19 (65.5) | 9 (31.0) | 20 (69.0) | 15 (51.7) | 14 (48.3) | 15 (51.7) | 14 (48.3) | 14 (48.3) | 15 (51.7) | 22 (75.9) | 7 (24.1) | 18 (62.1) | 11 (37.9) | 16 (55.2) | 13 (44.8) |
| | 250+ | ICT | 13 | 17 | 10 | 20 | 22 | 8 | 17 | 13 | 22 | 8 | 24 | 6 | 21 | 9 | 10 | 20 |

| Country | Enterprise size | Sector | Difficulties in estimating the returns on investment in AI applications | | Concerns related to data privacy, data protection or data security | | Scarcity of cloud computing solutions that guarantee data security and regulatory compliance | | Lack of clarity about the legal consequences in case of damage caused by the use of AI | | Lack of vendors of AI systems offering solutions tailored to your enterprise's needs | | Lack of external finance for investment to support AI adoption | | Reluctance of staff to adopt AI | | Difficulties to retrain or upskill staff | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| | | | (43.3) | (56.7) | (33.3) | (66.7) | (73.3) | (26.7) | (56.7) | (43.3) | (73.3) | (26.7) | (80.0) | (20.0) | (70.0) | (30.0) | (33.3) | (66.7) |
| | | MFT | 9<br>(30.0) | 21<br>(70.0) | 14<br>(46.7) | 16<br>(53.3) | 22<br>(73.3) | 8<br>(26.7) | 19<br>(63.3) | 11<br>(36.7) | 16<br>(53.3) | 14<br>(46.7) | 26<br>(86.7) | 4<br>(13.3) | 18<br>(60.0) | 12<br>(40.0) | 17<br>(56.7) | 13<br>(43.3) |

Note: MFT = Manufacturing. Numbers presented in parentheses are percentages.

## Table E.13. Q11 - In the last 12 months, has your enterprise recruited graduates in artificial intelligence, machine learning or related fields?

| Country | Enterprise size | Sector | No, because we did not have specific vacancies | No, we could not hire appropriate candidates | Yes, we were able to hire for our vacancies |
|---|---|---|---|---|---|
| CAN | 50-249 | ICT | 3 (10.0%) | 8 (26.7%) | 19 (63.3%) |
| | | Manufacturing | 3 (10.0%) | 6 (20.0%) | 21 (70.0%) |
| | 250+ | ICT | 4 (13.3%) | 6 (20.0%) | 20 (66.7%) |
| | | Manufacturing | 13 (43.3%) | 2 (6.7%) | 15 (50.0%) |
| DEU | 50-249 | ICT | 8 (26.7%) | 5 (16.7%) | 17 (56.7%) |
| | | Manufacturing | 7 (23.3%) | 9 (30.0%) | 14 (46.7%) |
| | 250+ | ICT | 5 (16.7%) | 4 (13.3%) | 21 (70.0%) |
| | | Manufacturing | 7 (23.3%) | 7 (23.3%) | 16 (53.3%) |
| FRA | 50-249 | ICT | 6 (20.0%) | 10 (33.3%) | 14 (46.7%) |
| | | Manufacturing | 0 (0.0%) | 1 (3.3%) | 29 (96.7%) |
| | 250+ | ICT | 3 (10.0%) | 3 (10.0%) | 24 (80.0%) |
| | | Manufacturing | 3 (10.0%) | 4 (13.3%) | 23 (76.7%) |
| GBR | 50-249 | ICT | 9 (30.0%) | 4 (13.3%) | 17 (56.7%) |
| | | Manufacturing | 9 (30.0%) | 1 (3.3%) | 20 (66.7%) |
| | 250+ | ICT | 7 (23.3%) | 4 (13.3%) | 19 (63.3%) |
| | | Manufacturing | 7 (23.3%) | 7 (23.3%) | 16 (53.3%) |
| ITA | 50-249 | ICT | 5 (16.7%) | 11 (36.7%) | 14 (46.7%) |
| | | Manufacturing | 8 (26.7%) | 9 (30.0%) | 13 (43.3%) |
| | 250+ | ICT | 6 (20.0%) | 8 (26.7%) | 16 (53.3%) |
| | | Manufacturing | 13 (43.3%) | 4 (13.3%) | 13 (43.3%) |
| JPN | 50-249 | ICT | 2 (6.7%) | 7 (23.3%) | 21 (70.0%) |
| | | Manufacturing | 3 (10.0%) | 3 (10.0%) | 24 (80.0%) |
| | 250+ | ICT | 6 (20.0%) | 7 (23.3%) | 17 (56.7%) |
| | | Manufacturing | 1 (3.3%) | 8 (26.7%) | 21 (70.0%) |
| USA | 50-249 | ICT | 5 (16.7%) | 6 (20.0%) | 19 (63.3%) |
| | | Manufacturing | 12 (40.0%) | 6 (20.0%) | 12 (40.0%) |
| | 250+ | ICT | 6 (20.0%) | 4 (13.3%) | 20 (66.7%) |
| | | Manufacturing | 11 (36.7%) | 2 (6.7%) | 17 (56.7%) |

## Table E.14. Q12 - In the past 12 months, has your enterprise experienced difficulties in understanding what skill sets to look for in new AI recruits?

| Country | Enterprise size | Sector | No | Yes |
|---|---|---|---|---|
| CAN | 50-249 | ICT | 14 (46.7%) | 16 (53.3%) |
| | | Manufacturing | 5 (16.7%) | 25 (83.3%) |
| | 250+ | ICT | 13 (43.3%) | 17 (56.7%) |
| | | Manufacturing | 20 (66.7%) | 10 (33.3%) |
| DEU | 50-249 | ICT | 14 (46.7%) | 16 (53.3%) |
| | | Manufacturing | 14 (46.7%) | 16 (53.3%) |
| | 250+ | ICT | 22 (73.3%) | 8 (26.7%) |
| | | Manufacturing | 12 (40.0%) | 18 (60.0%) |
| FRA | 50-249 | ICT | 14 (46.7%) | 16 (53.3%) |
| | | Manufacturing | 11 (36.7%) | 19 (63.3%) |
| | 250+ | ICT | 15 (50.0%) | 15 (50.0%) |
| | | Manufacturing | 14 (46.7%) | 16 (53.3%) |
| GBR | 50-249 | ICT | 13 (43.3%) | 17 (56.7%) |
| | | Manufacturing | 17 (56.7%) | 13 (43.3%) |
| | 250+ | ICT | 16 (53.3%) | 14 (46.7%) |
| | | Manufacturing | 16 (53.3%) | 14 (46.7%) |
| ITA | 50-249 | ICT | 13 (43.3%) | 17 (56.7%) |
| | | Manufacturing | 16 (53.3%) | 14 (46.7%) |
| | 250+ | ICT | 16 (53.3%) | 14 (46.7%) |
| | | Manufacturing | 22 (73.3%) | 8 (26.7%) |
| JPN | 50-249 | ICT | 15 (50.0%) | 15 (50.0%) |
| | | Manufacturing | 9 (30.0%) | 21 (70.0%) |
| | 250+ | ICT | 12 (40.0%) | 18 (60.0%) |
| | | Manufacturing | 10 (33.3%) | 20 (66.7%) |
| USA | 50-249 | ICT | 17 (56.7%) | 13 (43.3%) |
| | | Manufacturing | 22 (73.3%) | 8 (26.7%) |
| | 250+ | ICT | 18 (60.0%) | 12 (40.0%) |
| | | Manufacturing | 15 (50.0%) | 15 (50.0%) |

## Table E.15. Q13 - How helpful would you say the following types of support could be for your enterprise to strengthen staff skills in AI?

| Country | Enterprise size | Sector | Partnerships with educational and vocational institutions | | | | Tax allowances or tax credits for training in AI | | | | Support to develop qualification frameworks for graduates in the field of AI | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Moder-ately useful | Not useful at all | Slightly useful | Very useful | Moder-ately useful | Not useful at all | Slightly useful | Very useful | Moder-ately useful | Not useful at all | Slightly useful | Very useful |
| CAN | 50-249 | ICT | 12 (40.0%) | 0 (0.0%) | 5 (16.7%) | 13 (43.3%) | 14 (46.7%) | 2 (6.7%) | 8 (26.7%) | 6 (20.0%) | 14 (46.7%) | 0 (0.0%) | 5 (16.7%) | 11 (36.7%) |
| | | MFT | 11 (36.7%) | 0 (0.0%) | 2 (6.7%) | 17 (56.7%) | 16 (53.3%) | 1 (3.3%) | 5 (16.7%) | 8 (26.7%) | 14 (46.7%) | 0 (0.0%) | 2 (6.7%) | 14 (46.7%) |
| | 250+ | ICT | 12 (40.0%) | 1 (3.3%) | 4 (13.3%) | 13 (43.3%) | 9 (30.0%) | 5 (16.7%) | 3 (10.0%) | 13 (43.3%) | 13 (43.3%) | 1 (3.3%) | 4 (13.3%) | 12 (40.0%) |

| Country | Enterprise size | Sector | Partnerships with educational and vocational institutions | | | | Tax allowances or tax credits for training in AI | | | | Support to develop qualification frameworks for graduates in the field of AI | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Moder-ately useful | Not useful at all | Slightly useful | Very useful | Moder-ately useful | Not useful at all | Slightly useful | Very useful | Moder-ately useful | Not useful at all | Slightly useful | Very useful |
| | | MFT | 15 (50.0%) | 0 (0.0%) | 2 (6.7%) | 13 (43.3%) | 10 (33.3%) | 3 (10.0%) | 12 (40.0%) | 5 (16.7%) | 10 (33.3%) | 0 (0.0%) | 11 (36.7%) | 9 (30.0%) |
| DEU | 50-249 | ICT | 8 (26.7%) | 1 (3.3%) | 5 (16.7%) | 16 (53.3%) | 13 (43.3%) | 4 (13.3%) | 4 (13.3%) | 9 (30.0%) | 9 (30.0%) | 2 (6.7%) | 3 (10.0%) | 16 (53.3%) |
| | | MFT | 15 (50.0%) | 1 (3.3%) | 3 (10.0%) | 11 (36.7%) | 10 (33.3%) | 1 (3.3%) | 7 (23.3%) | 12 (40.0%) | 15 (50.0%) | 1 (3.3%) | 3 (10.0%) | 11 (36.7%) |
| | 250+ | ICT | 14 (46.7%) | 2 (6.7%) | 5 (16.7%) | 9 (30.0%) | 13 (43.3%) | 5 (16.7%) | 8 (26.7%) | 4 (13.3%) | 8 (26.7%) | 0 (0.0%) | 7 (23.3%) | 15 (50.0%) |
| | | MFT | 10 (33.3%) | 0 (0.0%) | 4 (13.3%) | 16 (53.3%) | 12 (40.0%) | 4 (13.3%) | 9 (30.0%) | 5 (16.7%) | 16 (53.3%) | 0 (0.0%) | 4 (13.3%) | 10 (33.3%) |
| FRA | 50-249 | ICT | 12 (40.0%) | 0 (0.0%) | 3 (10.0%) | 15 (50.0%) | 10 (33.3%) | 3 (10.0%) | 5 (16.7%) | 12 (40.0%) | 14 (46.7%) | 1 (3.3%) | 6 (20.0%) | 9 (30.0%) |
| | | MFT | 8 (26.7%) | 0 (0.0%) | 0 (0.0%) | 22 (73.3%) | 14 (46.7%) | 0 (0.0%) | 3 (10.0%) | 13 (43.3%) | 12 (40.0%) | 0 (0.0%) | 2 (6.7%) | 16 (53.3%) |
| | 250+ | ICT | 15 (50.0%) | 0 (0.0%) | 3 (10.0%) | 12 (40.0%) | 6 (20.0%) | 5 (16.7%) | 12 (40.0%) | 7 (23.3%) | 9 (30.0%) | 0 (0.0%) | 4 (13.3%) | 17 (56.7%) |
| | | MFT | 11 (36.7%) | 1 (3.3%) | 0 (0.0%) | 18 (60.0%) | 11 (36.7%) | 4 (13.3%) | 7 (23.3%) | 8 (26.7%) | 10 (33.3%) | 1 (3.3%) | 3 (10.0%) | 16 (53.3%) |
| GBR | 50-249 | ICT | 10 (33.3%) | 0 (0.0%) | 5 (16.7%) | 15 (50.0%) | 14 (46.7%) | 2 (6.7%) | 8 (26.7%) | 6 (20.0%) | 17 (56.7%) | 1 (3.3%) | 1 (3.3%) | 11 (36.7%) |
| | | MFT | 9 (30.0%) | 0 (0.0%) | 2 (6.7%) | 19 (63.3%) | 18 (60.0%) | 1 (3.3%) | 2 (6.7%) | 9 (30.0%) | 12 (40.0%) | 0 (0.0%) | 4 (13.3%) | 14 (46.7%) |
| | 250+ | ICT | 15 (50.0%) | 1 (3.3%) | 3 (10.0%) | 11 (36.7%) | 7 (23.3%) | 4 (13.3%) | 6 (20.0%) | 13 (43.3%) | 11 (36.7%) | 1 (3.3%) | 8 (26.7%) | 10 (33.3%) |
| | | MFT | 12 (40.0%) | 0 (0.0%) | 2 (6.7%) | 16 (53.3%) | 9 (30.0%) | 1 (3.3%) | 11 (36.7%) | 9 (30.0%) | 15 (50.0%) | 0 (0.0%) | 1 (3.3%) | 14 (46.7%) |
| ITA | 50-249 | ICT | 17 (56.7%) | 1 (3.3%) | 6 (20.0%) | 6 (20.0%) | 11 (36.7%) | 2 (6.7%) | 8 (26.7%) | 9 (30.0%) | 14 (46.7%) | 1 (3.3%) | 6 (20.0%) | 9 (30.0%) |
| | | MFT | 15 (50.0%) | 1 (3.3%) | 6 (20.0%) | 8 (26.7%) | 12 (40.0%) | 2 (6.7%) | 5 (16.7%) | 11 (36.7%) | 17 (56.7%) | 0 (0.0%) | 5 (16.7%) | 8 (26.7%) |
| | 250+ | ICT | 15 (50.0%) | 0 (0.0%) | 10 (33.3%) | 5 (16.7%) | 11 (36.7%) | 2 (6.7%) | 5 (16.7%) | 12 (40.0%) | 9 (30.0%) | 1 (3.3%) | 6 (20.0%) | 14 (46.7%) |
| | | MFT | 11 (36.7%) | 0 (0.0%) | 5 (16.7%) | 14 (46.7%) | 8 (26.7%) | 4 (13.3%) | 10 (33.3%) | 8 (26.7%) | 14 (46.7%) | 0 (0.0%) | 3 (10.0%) | 13 (43.3%) |
| JPN | 50-249 | ICT | 16 (53.3%) | 0 (0.0%) | 4 (13.3%) | 10 (33.3%) | 9 (30.0%) | 1 (3.3%) | 6 (20.0%) | 14 (46.7%) | 14 (46.7%) | 0 (0.0%) | 2 (6.7%) | 14 (46.7%) |
| | | MFT | 13 (43.3%) | 0 (0.0%) | 2 (6.7%) | 15 (50.0%) | 14 (46.7%) | 0 (0.0%) | 2 (6.7%) | 14 (46.7%) | 14 (46.7%) | 1 (3.3%) | 1 (3.3%) | 14 (46.7%) |
| | 250+ | ICT | 14 (46.7%) | 0 (0.0%) | 6 (20.0%) | 10 (33.3%) | 6 (20.0%) | 7 (23.3%) | 10 (33.3%) | 7 (23.3%) | 9 (30.0%) | 1 (3.3%) | 6 (20.0%) | 14 (46.7%) |
| | | MFT | 18 (60.0%) | 0 (0.0%) | 3 (10.0%) | 9 (30.0%) | 13 (43.3%) | 5 (16.7%) | 5 (16.7%) | 7 (23.3%) | 13 (43.3%) | 2 (6.7%) | 4 (13.3%) | 11 (36.7%) |
| USA | 50-249 | ICT | 13 (43.3%) | 2 (6.7%) | 8 (26.7%) | 7 (23.3%) | 9 (30.0%) | 6 (20.0%) | 9 (30.0%) | 6 (20.0%) | 9 (30.0%) | 1 (3.3%) | 12 (40.0%) | 8 (26.7%) |
| | | MFT | 15 (50.0%) | 1 (3.3%) | 6 (20.0%) | 8 (26.7%) | 10 (33.3%) | 4 (13.3%) | 7 (23.3%) | 9 (30.0%) | 13 (43.3%) | 1 (3.3%) | 8 (26.7%) | 8 (26.7%) |
| | 250+ | ICT | 13 (43.3%) | 2 (6.7%) | 8 (26.7%) | 7 (23.3%) | 12 (40.0%) | 1 (3.3%) | 10 (33.3%) | 7 (23.3%) | 17 (56.7%) | 1 (3.3%) | 7 (23.3%) | 5 (16.7%) |
| | | MFT | 7 (23.3%) | 1 (3.3%) | 7 (23.3%) | 15 (50.0%) | 8 (26.7%) | 7 (23.3%) | 6 (20.0%) | 9 (30.0%) | 9 (30.0%) | 4 (13.3%) | 7 (23.3%) | 10 (33.3%) |

Note: MFT = Manufacturing.

## Table E.16. Q14 - In your country, a number of public and public-private organisations, such as [X], work to speed up the adoption of digital technologies. In using AI in your enterprise, how helpful would the following types of services provided by the public sector be?

| Country | Enterprise size | Sector | Information on and examples of business use cases in your industry | | | | Information on expected rates of return to investments in AI | | | | Information on available and reliable technology vendors | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| CAN | 50-249 | ICT | 8 (26.7) | 9 (30.0) | 0 (0.0) | 13 (43.3) | 7 (23.3) | 20 (66.7) | 0 (0.0) | 3 (10.0) | 3 (10.0) | 9 (30.0) | 1 (3.3) | 17 (56.7) |
| | | MFT | 2 (6.7) | 13 (43.3) | 0 (0.0) | 15 (50.0) | 2 (6.7) | 19 (63.3) | 0 (0.0) | 9 (30.0) | 3 (10.0) | 10 (33.3) | 0 (0.0) | 17 (56.7) |
| | 250+ | ICT | 7 (23.3) | 9 (30.0) | 0 (0.0) | 14 (46.7) | 3 (10.0) | 15 (50.0) | 2 (6.7) | 10 (33.3) | 4 (13.3) | 11 (36.7) | 0 (0.0) | 15 (50.0) |
| | | MFT | 2 (6.7) | 13 (43.3) | 0 (0.0) | 15 (50.0) | 6 (20.0) | 11 (36.7) | 0 (0.0) | 13 (43.3) | 9 (30.0) | 9 (30.0) | 1 (3.3) | 11 (36.7) |
| DEU | 50-249 | ICT | 4 (13.3) | 9 (30.0) | 2 (6.7) | 15 (50.0) | 5 (16.7) | 13 (43.3) | 3 (10.0) | 9 (30.0) | 3 (10.0) | 14 (46.7) | 3 (10.0) | 10 (33.3) |
| | | MFT | 4 (13.3) | 11 (36.7) | 0 (0.0) | 15 (50.0) | 5 (16.7) | 19 (63.3) | 0 (0.0) | 6 (20.0) | 5 (16.7) | 11 (36.7) | 0 (0.0) | 14 (46.7) |
| | 250+ | ICT | 7 (23.3) | 14 (46.7) | 2 (6.7) | 7 (23.3) | 5 (16.7) | 13 (43.3) | 1 (3.3) | 11 (36.7) | 3 (10.0) | 15 (50.0) | 2 (6.7) | 10 (33.3) |
| | | MFT | 4 (13.3) | 13 (43.3) | 1 (3.3) | 12 (40.0) | 3 (10.0) | 16 (53.3) | 1 (3.3) | 10 (33.3) | 8 (26.7) | 14 (46.7) | 0 (0.0) | 8 (26.7) |
| FRA | 50-249 | ICT | 8 (26.7) | 10 (33.3) | 0 (0.0) | 12 (40.0) | 3 (10.0) | 9 (30.0) | 1 (3.3) | 17 (56.7) | 3 (10.0) | 9 (30.0) | 0 (0.0) | 18 (60.0) |
| | | MFT | 1 (3.3) | 10 (33.3) | 0 (0.0) | 19 (63.3) | 3 (10.0) | 16 (53.3) | 0 (0.0) | 11 (36.7) | 0 (0.0) | 19 (63.3) | 0 (0.0) | 11 (36.7) |
| | 250+ | ICT | 5 (16.7) | 14 (46.7) | 1 (3.3) | 10 (33.3) | 3 (10.0) | 15 (50.0) | 3 (10.0) | 9 (30.0) | 6 (20.0) | 12 (40.0) | 1 (3.3) | 11 (36.7) |
| | | MFT | 2 (6.7) | 13 (43.3) | 0 (0.0) | 15 (50.0) | 5 (16.7) | 10 (33.3) | 1 (3.3) | 14 (46.7) | 6 (20.0) | 12 (40.0) | 0 (0.0) | 12 (40.0) |
| GBR | 50-249 | ICT | 7 (23.3) | 11 (36.7) | 0 (0.0) | 12 (40.0) | 4 (13.3) | 15 (50.0) | 0 (0.0) | 11 (36.7) | 5 (16.7) | 15 (50.0) | 1 (3.3) | 9 (30.0) |
| | | MFT | 1 (3.3) | 5 (16.7) | 0 (0.0) | 24 (80.0) | 1 (3.3) | 19 (63.3) | 0 (0.0) | 10 (33.3) | 4 (13.3) | 14 (46.7) | 0 (0.0) | 12 (40.0) |
| | 250+ | ICT | 6 (20.0) | 9 (30.0) | 3 (10.0) | 12 (40.0) | 7 (23.3) | 12 (40.0) | 2 (6.7) | 9 (30.0) | 2 (6.7) | 14 (46.7) | 1 (3.3) | 13 (43.3) |
| | | MFT | 3 (10.0) | 11 (36.7) | 0 (0.0) | 16 (53.3) | 3 (10.0) | 19 (63.3) | 1 (3.3) | 7 (23.3) | 4 (13.3) | 12 (40.0) | 0 (0.0) | 14 (46.7) |
| ITA | 50-249 | ICT | 2 (6.7) | 20 (66.7) | 1 (3.3) | 7 (23.3) | 4 (13.3) | 9 (30.0) | 1 (3.3) | 16 (53.3) | 5 (16.7) | 16 (53.3) | 1 (3.3) | 8 (26.7) |
| | | MFT | 4 (13.3) | 11 (36.7) | 0 (0.0) | 15 (50.0) | 3 (10.0) | 20 (66.7) | 0 (0.0) | 7 (23.3) | 2 (6.7) | 9 (30.0) | 1 (3.3) | 18 (60.0) |
| | 250+ | ICT | 6 (20.0) | 15 (50.0) | 1 (3.3) | 8 (26.7) | 4 (13.3) | 10 (33.3) | 2 (6.7) | 14 (46.7) | 7 (23.3) | 12 (40.0) | 1 (3.3) | 10 (33.3) |
| | | MFT | 5 (16.7) | 14 (46.7) | 0 (0.0) | 11 (36.7) | 3 (10.0) | 12 (40.0) | 0 (0.0) | 15 (50.0) | 6 (20.0) | 9 (30.0) | 0 (0.0) | 15 (50.0) |
| JPN | 50-249 | ICT | 6 (20.0) | 17 (56.7) | 0 (0.0) | 7 (23.3) | 6 (20.0) | 15 (50.0) | 1 (3.3) | 8 (26.7) | 6 (20.0) | 12 (40.0) | 1 (3.3) | 11 (36.7) |
| | | MFT | 3 (10.0) | 13 (43.3) | 0 (0.0) | 14 (46.7) | 2 (6.7) | 11 (36.7) | 0 (0.0) | 17 (56.7) | 4 (13.3) | 14 (46.7) | 0 (0.0) | 12 (40.0) |
| | 250+ | ICT | 7 (23.3) | 15 (50.0) | 0 (0.0) | 8 (26.7) | 4 (13.3) | 14 (46.7) | 0 (0.0) | 12 (40.0) | 6 (20.0) | 14 (46.7) | 1 (3.3) | 9 (30.0) |

| Country | Enterprise size | Sector | Information on and examples of business use cases in your industry | | | | Information on expected rates of return to investments in AI | | | | Information on available and reliable technology vendors | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| | | MFT | 6 (20.0) | 14 (46.7) | 0 (0.0) | 10 (33.3) | 6 (20.0) | 16 (53.3) | 1 (3.3) | 7 (23.3) | 4 (13.3) | 9 (30.0) | 1 (3.3) | 16 (53.3) |
| USA | 50-249 | ICT | 6 (20.0) | 9 (30.0) | 4 (13.3) | 11 (36.7) | 8 (26.7) | 11 (36.7) | 2 (6.7) | 9 (30.0) | 10 (33.3) | 8 (26.7) | 4 (13.3) | 8 (26.7) |
| | | MFT | 8 (26.7) | 12 (40.0) | 0 (0.0) | 10 (33.3) | 5 (16.7) | 15 (50.0) | 2 (6.7) | 8 (26.7) | 8 (26.7) | 11 (36.7) | 0 (0.0) | 11 (36.7) |
| | 250+ | ICT | 6 (20.0) | 11 (36.7) | 1 (3.3) | 12 (40.0) | 1 (3.3) | 13 (43.3) | 2 (6.7) | 14 (46.7) | 8 (26.7) | 14 (46.7) | 0 (0.0) | 8 (26.7) |
| | | MFT | 5 (16.7) | 12 (40.0) | 2 (6.7) | 11 (36.7) | 6 (20.0) | 10 (33.3) | 2 (6.7) | 12 (40.0) | 4 (13.3) | 18 (60.0) | 1 (3.3) | 7 (23.3) |

Note: MFT = Manufacturing. Numbers presented in parentheses are percentages.

## Table E.17. Q14 - In your country, a number of public and public-private organisations, such as [X], work to speed up the adoption of digital technologies. In using AI in your enterprise, how helpful would the following types of services provided by the public sector be? (continued)

| Country | Enterprise size | Sector | Information on available and reliable sources of private-sector advice and expertise | | | | Certification or accreditation schemes for AI solution providers | | | | Information on current or forthcoming regulations around data or AI | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| CAN | 50-249 | ICT | 2 (6.7%) | 14 (46.7%) | 0 (0.0%) | 14 (46.7%) | 7 (23.3%) | 12 (40.0%) | 0 (0.0%) | 11 (36.7%) | 6 (20.0%) | 14 (46.7%) | 0 (0.0%) | 10 (33.3%) |
| | | MFT | 3 (10.0%) | 13 (43.3%) | 0 (0.0%) | 14 (46.7%) | 3 (10.0%) | 15 (50.0%) | 0 (0.0%) | 12 (40.0%) | 6 (20.0%) | 12 (40.0%) | 0 (0.0%) | 12 (40.0%) |
| | 250+ | ICT | 7 (23.3%) | 12 (40.0%) | 1 (3.3%) | 10 (33.3%) | 8 (26.7%) | 13 (43.3%) | 3 (10.0%) | 6 (20.0%) | 5 (16.7%) | 14 (46.7%) | 0 (0.0%) | 11 (36.7%) |
| | | MFT | 4 (13.3%) | 11 (36.7%) | 1 (3.3%) | 14 (46.7%) | 9 (30.0%) | 16 (53.3%) | 1 (3.3%) | 4 (13.3%) | 3 (10.0%) | 9 (30.0%) | 1 (3.3%) | 17 (56.7%) |
| DEU | 50-249 | ICT | 5 (16.7%) | 13 (43.3%) | 1 (3.3%) | 11 (36.7%) | 8 (26.7%) | 14 (46.7%) | 1 (3.3%) | 7 (23.3%) | 5 (16.7%) | 12 (40.0%) | 0 (0.0%) | 13 (43.3%) |
| | | MFT | 7 (23.3%) | 10 (33.3%) | 0 (0.0%) | 13 (43.3%) | 3 (10.0%) | 17 (56.7%) | 0 (0.0%) | 10 (33.3%) | 4 (13.3%) | 13 (43.3%) | 0 (0.0%) | 13 (43.3%) |
| | 250+ | ICT | 5 (16.7%) | 15 (50.0%) | 1 (3.3%) | 9 (30.0%) | 5 (16.7%) | 12 (40.0%) | 2 (6.7%) | 11 (36.7%) | 7 (23.3%) | 12 (40.0%) | 1 (3.3%) | 10 (33.3%) |
| | | MFT | 8 (26.7%) | 13 (43.3%) | 1 (3.3%) | 8 (26.7%) | 9 (30.0%) | 12 (40.0%) | 2 (6.7%) | 7 (23.3%) | 5 (16.7%) | 10 (33.3%) | 1 (3.3%) | 14 (46.7%) |
| FRA | 50-249 | ICT | 10 (33.3%) | 13 (43.3%) | 0 (0.0%) | 7 (23.3%) | 6 (20.0%) | 12 (40.0%) | 0 (0.0%) | 12 (40.0%) | 3 (10.0%) | 14 (46.7%) | 0 (0.0%) | 13 (43.3%) |
| | | MFT | 1 (3.3%) | 8 (26.7%) | 0 (0.0%) | 21 (70.0%) | 2 (6.7%) | 14 (46.7%) | 0 (0.0%) | 14 (46.7%) | 0 (0.0%) | 18 (60.0%) | 0 (0.0%) | 12 (40.0%) |
| | 250+ | ICT | 8 (26.7%) | 15 (50.0%) | 1 (3.3%) | 6 (20.0%) | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) | 0 (0.0%) | 15 (50.0%) | 0 (0.0%) | 15 (50.0%) |
| | | MFT | 3 (10.0%) | 13 (43.3%) | 0 (0.0%) | 14 (46.7%) | 2 (6.7%) | 9 (30.0%) | 3 (10.0%) | 16 (53.3%) | 3 (10.0%) | 10 (33.3%) | 1 (3.3%) | 16 (53.3%) |

| Country | Enterprise size | Sector | Information on available and reliable sources of private-sector advice and expertise | | | | Certification or accreditation schemes for AI solution providers | | | | Information on current or forthcoming regulations around data or AI | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| GBR | 50-249 | ICT | 7 (23.3%) | 15 (50.0%) | 1 (3.3%) | 7 (23.3%) | 2 (6.7%) | 15 (50.0%) | 1 (3.3%) | 12 (40.0%) | 7 (23.3%) | 8 (26.7%) | 0 (0.0%) | 15 (50.0%) |
| | | MFT | 6 (20.0%) | 11 (36.7%) | 0 (0.0%) | 13 (43.3%) | 8 (26.7%) | 14 (46.7%) | 0 (0.0%) | 8 (26.7%) | 3 (10.0%) | 16 (53.3%) | 0 (0.0%) | 11 (36.7%) |
| | 250+ | ICT | 4 (13.3%) | 13 (43.3%) | 2 (6.7%) | 11 (36.7%) | 9 (30.0%) | 11 (36.7%) | 0 (0.0%) | 10 (33.3%) | 4 (13.3%) | 11 (36.7%) | 1 (3.3%) | 14 (46.7%) |
| | | MFT | 10 (33.3%) | 13 (43.3%) | 0 (0.0%) | 7 (23.3%) | 8 (26.7%) | 12 (40.0%) | 1 (3.3%) | 9 (30.0%) | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) |
| ITA | 50-249 | ICT | 5 (16.7%) | 16 (53.3%) | 1 (3.3%) | 8 (26.7%) | 6 (20.0%) | 14 (46.7%) | 1 (3.3%) | 9 (30.0%) | 2 (6.7%) | 18 (60.0%) | 1 (3.3%) | 9 (30.0%) |
| | | MFT | 5 (16.7%) | 13 (43.3%) | 0 (0.0%) | 12 (40.0%) | 6 (20.0%) | 16 (53.3%) | 0 (0.0%) | 8 (26.7%) | 4 (13.3%) | 15 (50.0%) | 0 (0.0%) | 11 (36.7%) |
| | 250+ | ICT | 5 (16.7%) | 14 (46.7%) | 1 (3.3%) | 10 (33.3%) | 3 (10.0%) | 17 (56.7%) | 2 (6.7%) | 8 (26.7%) | 6 (20.0%) | 18 (60.0%) | 1 (3.3%) | 5 (16.7%) |
| | | MFT | 7 (23.3%) | 18 (60.0%) | 0 (0.0%) | 5 (16.7%) | 7 (23.3%) | 14 (46.7%) | 2 (6.7%) | 7 (23.3%) | 5 (16.7%) | 7 (23.3%) | 2 (6.7%) | 16 (53.3%) |
| JPN | 50-249 | ICT | 5 (16.7%) | 10 (33.3%) | 0 (0.0%) | 15 (50.0%) | 5 (16.7%) | 17 (56.7%) | 0 (0.0%) | 8 (26.7%) | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) |
| | | MFT | 3 (10.0%) | 12 (40.0%) | 0 (0.0%) | 15 (50.0%) | 4 (13.3%) | 15 (50.0%) | 0 (0.0%) | 11 (36.7%) | 4 (13.3%) | 12 (40.0%) | 0 (0.0%) | 14 (46.7%) |
| | 250+ | ICT | 6 (20.0%) | 14 (46.7%) | 0 (0.0%) | 10 (33.3%) | 5 (16.7%) | 17 (56.7%) | 0 (0.0%) | 8 (26.7%) | 3 (10.0%) | 14 (46.7%) | 0 (0.0%) | 13 (43.3%) |
| | | MFT | 2 (6.7%) | 15 (50.0%) | 3 (10.0%) | 10 (33.3%) | 7 (23.3%) | 11 (36.7%) | 1 (3.3%) | 11 (36.7%) | 7 (23.3%) | 14 (46.7%) | 1 (3.3%) | 8 (26.7%) |
| USA | 50-249 | ICT | 8 (26.7%) | 12 (40.0%) | 3 (10.0%) | 7 (23.3%) | 10 (33.3%) | 9 (30.0%) | 5 (16.7%) | 6 (20.0%) | 7 (23.3%) | 8 (26.7%) | 4 (13.3%) | 11 (36.7%) |
| | | MFT | 6 (20.0%) | 15 (50.0%) | 1 (3.3%) | 8 (26.7%) | 6 (20.0%) | 13 (43.3%) | 3 (10.0%) | 8 (26.7%) | 5 (16.7%) | 15 (50.0%) | 0 (0.0%) | 10 (33.3%) |
| | 250+ | ICT | 8 (26.7%) | 17 (56.7%) | 0 (0.0%) | 5 (16.7%) | 8 (26.7%) | 12 (40.0%) | 2 (6.7%) | 8 (26.7%) | 4 (13.3%) | 15 (50.0%) | 0 (0.0%) | 11 (36.7%) |
| | | MFT | 5 (16.7%) | 16 (53.3%) | 2 (6.7%) | 7 (23.3%) | 11 (36.7%) | 11 (36.7%) | 2 (6.7%) | 6 (20.0%) | 11 (36.7%) | 4 (13.3%) | 3 (10.0%) | 12 (40.0%) |

Note: MFT = Manufacturing.

## Table E.18. Q15 - How helpful would you say the following initiatives provided by the public sector could be for the adoption of AI in your enterprise?

| Country | Enterprise size | Sector | Investing in university education and vocational training in fields related to AI | | | | Investing in retraining and lifelong learning for employees who work with AI | | | | Improving understanding of AI among government officials | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| CAN | 50-249 | ICT | 6 (20.0%) | 11 (36.7%) | 0 (0.0%) | 13 (43.3%) | 1 (3.3%) | 18 (60.0%) | 0 (0.0%) | 11 (36.7%) | 7 (23.3%) | 14 (46.7%) | 1 (3.3%) | 8 (26.7%) |
| | | MFT | 2 | 13 | 0 | 15 | 3 | 14 | 0 | 13 | 6 | 9 | 0 | 15 |

| Country | Enterprise size | Sector | Investing in university education and vocational training in fields related to AI | | | | Investing in retraining and lifelong learning for employees who work with AI | | | | Improving understanding of AI among government officials | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| | | | (6.7%) | (43.3%) | (0.0%) | (50.0%) | (10.0%) | (46.7%) | (0.0%) | (43.3%) | (20.0%) | (30.0%) | (0.0%) | (50.0%) |
| | 250+ | ICT | 3 (10.0%) | 16 (53.3%) | 1 (3.3%) | 10 (33.3%) | 3 (10.0%) | 9 (30.0%) | 1 (3.3%) | 17 (56.7%) | 8 (26.7%) | 10 (33.3%) | 3 (10.0%) | 9 (30.0%) |
| | | MFT | 5 (16.7%) | 13 (43.3%) | 1 (3.3%) | 11 (36.7%) | 6 (20.0%) | 10 (33.3%) | 0 (0.0%) | 14 (46.7%) | 6 (20.0%) | 10 (33.3%) | 2 (6.7%) | 12 (40.0%) |
| DEU | 50-249 | ICT | 4 (13.3%) | 11 (36.7%) | 2 (6.7%) | 13 (43.3%) | 2 (6.7%) | 14 (46.7%) | 0 (0.0%) | 14 (46.7%) | 6 (20.0%) | 11 (36.7%) | 3 (10.0%) | 10 (33.3%) |
| | | MFT | 2 (6.7%) | 20 (66.7%) | 0 (0.0%) | 8 (26.7%) | 2 (6.7%) | 15 (50.0%) | 0 (0.0%) | 13 (43.3%) | 8 (26.7%) | 11 (36.7%) | 1 (3.3%) | 10 (33.3%) |
| | 250+ | ICT | 4 (13.3%) | 15 (50.0%) | 1 (3.3%) | 10 (33.3%) | 6 (20.0%) | 9 (30.0%) | 0 (0.0%) | 15 (50.0%) | 9 (30.0%) | 5 (16.7%) | 0 (0.0%) | 16 (53.3%) |
| | | MFT | 4 (13.3%) | 15 (50.0%) | 1 (3.3%) | 10 (33.3%) | 3 (10.0%) | 15 (50.0%) | 2 (6.7%) | 10 (33.3%) | 7 (23.3%) | 11 (36.7%) | 3 (10.0%) | 9 (30.0%) |
| FRA | 50-249 | ICT | 6 (20.0%) | 10 (33.3%) | 0 (0.0%) | 14 (46.7%) | 4 (13.3%) | 16 (53.3%) | 0 (0.0%) | 10 (33.3%) | 4 (13.3%) | 11 (36.7%) | 0 (0.0%) | 15 (50.0%) |
| | | MFT | 1 (3.3%) | 10 (33.3%) | 0 (0.0%) | 19 (63.3%) | 0 (0.0%) | 13 (43.3%) | 0 (0.0%) | 17 (56.7%) | 0 (0.0%) | 19 (63.3%) | 0 (0.0%) | 11 (36.7%) |
| | 250+ | ICT | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) | 6 (20.0%) | 10 (33.3%) | 1 (3.3%) | 13 (43.3%) |
| | | MFT | 2 (6.7%) | 11 (36.7%) | 0 (0.0%) | 17 (56.7%) | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) | 4 (13.3%) | 13 (43.3%) | 2 (6.7%) | 11 (36.7%) |
| GBR | 50-249 | ICT | 7 (23.3%) | 14 (46.7%) | 0 (0.0%) | 9 (30.0%) | 5 (16.7%) | 13 (43.3%) | 0 (0.0%) | 12 (40.0%) | 8 (26.7%) | 13 (43.3%) | 0 (0.0%) | 9 (30.0%) |
| | | MFT | 4 (13.3%) | 6 (20.0%) | 0 (0.0%) | 20 (66.7%) | 0 (0.0%) | 16 (53.3%) | 0 (0.0%) | 14 (46.7%) | 4 (13.3%) | 11 (36.7%) | 0 (0.0%) | 15 (50.0%) |
| | 250+ | ICT | 4 (13.3%) | 15 (50.0%) | 0 (0.0%) | 11 (36.7%) | 5 (16.7%) | 16 (53.3%) | 0 (0.0%) | 9 (30.0%) | 6 (20.0%) | 10 (33.3%) | 3 (10.0%) | 11 (36.7%) |
| | | MFT | 1 (3.3%) | 14 (46.7%) | 0 (0.0%) | 15 (50.0%) | 5 (16.7%) | 14 (46.7%) | 0 (0.0%) | 11 (36.7%) | 5 (16.7%) | 13 (43.3%) | 0 (0.0%) | 12 (40.0%) |
| ITA | 50-249 | ICT | 5 (16.7%) | 16 (53.3%) | 2 (6.7%) | 7 (23.3%) | 1 (3.3%) | 10 (33.3%) | 1 (3.3%) | 18 (60.0%) | 6 (20.0%) | 17 (56.7%) | 1 (3.3%) | 6 (20.0%) |
| | | MFT | 9 (30.0%) | 12 (40.0%) | 0 (0.0%) | 9 (30.0%) | 2 (6.7%) | 11 (36.7%) | 1 (3.3%) | 16 (53.3%) | 7 (23.3%) | 17 (56.7%) | 0 (0.0%) | 6 (20.0%) |
| | 250+ | ICT | 7 (23.3%) | 16 (53.3%) | 0 (0.0%) | 7 (23.3%) | 5 (16.7%) | 12 (40.0%) | 0 (0.0%) | 13 (43.3%) | 9 (30.0%) | 9 (30.0%) | 1 (3.3%) | 11 (36.7%) |
| | | MFT | 3 (10.0%) | 16 (53.3%) | 1 (3.3%) | 10 (33.3%) | 2 (6.7%) | 8 (26.7%) | 1 (3.3%) | 19 (63.3%) | 7 (23.3%) | 13 (43.3%) | 0 (0.0%) | 10 (33.3%) |
| JPN | 50-249 | ICT | 10 (33.3%) | 15 (50.0%) | 1 (3.3%) | 4 (13.3%) | 5 (16.7%) | 10 (33.3%) | 1 (3.3%) | 14 (46.7%) | 10 (33.3%) | 13 (43.3%) | 0 (0.0%) | 7 (23.3%) |
| | | MFT | 3 (10.0%) | 6 (20.0%) | 1 (3.3%) | 20 (66.7%) | 3 (10.0%) | 11 (36.7%) | 0 (0.0%) | 16 (53.3%) | 2 (6.7%) | 20 (66.7%) | 0 (0.0%) | 8 (26.7%) |
| | 250+ | ICT | 5 (16.7%) | 17 (56.7%) | 0 (0.0%) | 8 (26.7%) | 7 (23.3%) | 9 (30.0%) | 1 (3.3%) | 13 (43.3%) | 9 (30.0%) | 12 (40.0%) | 1 (3.3%) | 8 (26.7%) |
| | | MFT | 7 (23.3%) | 12 (40.0%) | 2 (6.7%) | 9 (30.0%) | 6 (20.0%) | 12 (40.0%) | 1 (3.3%) | 11 (36.7%) | 8 (26.7%) | 9 (30.0%) | 3 (10.0%) | 10 (33.3%) |
| USA | 50-249 | ICT | 6 (20.0%) | 12 (40.0%) | 2 (6.7%) | 10 (33.3%) | 4 (13.3%) | 15 (50.0%) | 2 (6.7%) | 9 (30.0%) | 4 (13.3%) | 12 (40.0%) | 4 (13.3%) | 10 (33.3%) |
| | | MFT | 9 (30.0%) | 11 (36.7%) | 0 (0.0%) | 10 (33.3%) | 3 (10.0%) | 12 (40.0%) | 0 (0.0%) | 15 (50.0%) | 12 (40.0%) | 5 (16.7%) | 2 (6.7%) | 11 (36.7%) |
| | 250+ | ICT | 8 | 14 | 2 | 6 | 6 | 12 | 1 | 11 | 9 | 11 | 2 | 8 |

| Country | Enterprise size | Sector | Investing in university education and vocational training in fields related to AI | | | | Investing in retraining and lifelong learning for employees who work with AI | | | | Improving understanding of AI among government officials | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| | | | (26.7%) | (46.7%) | (6.7%) | (20.0%) | (20.0%) | (40.0%) | (3.3%) | (36.7%) | (30.0%) | (36.7%) | (6.7%) | (26.7%) |
| | | MFT | 5 (16.7%) | 13 (43.3%) | 2 (6.7%) | 10 (33.3%) | 5 (16.7%) | 12 (40.0%) | 2 (6.7%) | 11 (36.7%) | 8 (26.7%) | 14 (46.7%) | 3 (10.0%) | 5 (16.7%) |

Note: MFT = Manufacturing.

## Table E.19. Q15 - How helpful would you say the following initiatives provided by the public sector could be for the adoption of AI in your enterprise? (continued)

| Country | Enterprise size | Sector | Gathering and publishing administrative public datasets | | | | Promoting a competitive AI vendor market | | | | Upgrading IT infrastructure, such as high-speed broadband | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| CAN | 50-249 | ICT | 10 (33.3%) | 11 (36.7%) | 0 (0.0%) | 9 (30.0%) | 2 (6.7%) | 19 (63.3%) | 2 (6.7%) | 7 (23.3%) | 12 (40.0%) | 5 (16.7%) | 0 (0.0%) | 13 (43.3%) |
| | | MFT | 9 (30.0%) | 9 (30.0%) | 0 (0.0%) | 12 (40.0%) | 5 (16.7%) | 14 (46.7%) | 1 (3.3%) | 10 (33.3%) | 3 (10.0%) | 18 (60.0%) | 0 (0.0%) | 9 (30.0%) |
| | 250+ | ICT | 8 (26.7%) | 13 (43.3%) | 2 (6.7%) | 7 (23.3%) | 9 (30.0%) | 14 (46.7%) | 1 (3.3%) | 6 (20.0%) | 3 (10.0%) | 12 (40.0%) | 1 (3.3%) | 14 (46.7%) |
| | | MFT | 10 (33.3%) | 11 (36.7%) | 0 (0.0%) | 9 (30.0%) | 7 (23.3%) | 12 (40.0%) | 2 (6.7%) | 9 (30.0%) | 7 (23.3%) | 11 (36.7%) | 1 (3.3%) | 11 (36.7%) |
| DEU | 50-249 | ICT | 7 (23.3%) | 13 (43.3%) | 1 (3.3%) | 9 (30.0%) | 6 (20.0%) | 14 (46.7%) | 1 (3.3%) | 9 (30.0%) | 6 (20.0%) | 8 (26.7%) | 0 (0.0%) | 16 (53.3%) |
| | | MFT | 9 (30.0%) | 13 (43.3%) | 0 (0.0%) | 8 (26.7%) | 2 (6.7%) | 17 (56.7%) | 0 (0.0%) | 11 (36.7%) | 5 (16.7%) | 15 (50.0%) | 0 (0.0%) | 10 (33.3%) |
| | 250+ | ICT | 9 (30.0%) | 11 (36.7%) | 0 (0.0%) | 10 (33.3%) | 5 (16.7%) | 16 (53.3%) | 0 (0.0%) | 9 (30.0%) | 7 (23.3%) | 11 (36.7%) | 0 (0.0%) | 12 (40.0%) |
| | | MFT | 4 (13.3%) | 16 (53.3%) | 3 (10.0%) | 7 (23.3%) | 8 (26.7%) | 12 (40.0%) | 1 (3.3%) | 9 (30.0%) | 7 (23.3%) | 12 (40.0%) | 3 (10.0%) | 8 (26.7%) |
| FRA | 50-249 | ICT | 8 (26.7%) | 12 (40.0%) | 0 (0.0%) | 10 (33.3%) | 6 (20.0%) | 13 (43.3%) | 0 (0.0%) | 11 (36.7%) | 6 (20.0%) | 11 (36.7%) | 2 (6.7%) | 11 (36.7%) |
| | | MFT | 1 (3.3%) | 16 (53.3%) | 0 (0.0%) | 13 (43.3%) | 2 (6.7%) | 12 (40.0%) | 0 (0.0%) | 16 (53.3%) | 1 (3.3%) | 14 (46.7%) | 0 (0.0%) | 15 (50.0%) |
| | 250+ | ICT | 6 (20.0%) | 11 (36.7%) | 1 (3.3%) | 12 (40.0%) | 8 (26.7%) | 14 (46.7%) | 2 (6.7%) | 6 (20.0%) | 10 (33.3%) | 9 (30.0%) | 3 (10.0%) | 8 (26.7%) |
| | | MFT | 2 (6.7%) | 13 (43.3%) | 1 (3.3%) | 14 (46.7%) | 3 (10.0%) | 14 (46.7%) | 1 (3.3%) | 12 (40.0%) | 3 (10.0%) | 9 (30.0%) | 2 (6.7%) | 16 (53.3%) |
| GBR | 50-249 | ICT | 6 (20.0%) | 13 (43.3%) | 0 (0.0%) | 11 (36.7%) | 6 (20.0%) | 13 (43.3%) | 1 (3.3%) | 10 (33.3%) | 6 (20.0%) | 10 (33.3%) | 2 (6.7%) | 12 (40.0%) |
| | | MFT | 4 (13.3%) | 12 (40.0%) | 0 (0.0%) | 14 (46.7%) | 8 (26.7%) | 13 (43.3%) | 0 (0.0%) | 9 (30.0%) | 8 (26.7%) | 12 (40.0%) | 1 (3.3%) | 9 (30.0%) |
| | 250+ | ICT | 7 (23.3%) | 12 (40.0%) | 1 (3.3%) | 10 (33.3%) | 5 (16.7%) | 14 (46.7%) | 0 (0.0%) | 11 (36.7%) | 6 (20.0%) | 13 (43.3%) | 1 (3.3%) | 10 (33.3%) |
| | | MFT | 6 (20.0%) | 11 (36.7%) | 2 (6.7%) | 11 (36.7%) | 4 (13.3%) | 12 (40.0%) | 1 (3.3%) | 13 (43.3%) | 4 (13.3%) | 13 (43.3%) | 0 (0.0%) | 13 (43.3%) |

| Country | Enterprise size | Sector | Gathering and publishing administrative public datasets | | | | Promoting a competitive AI vendor market | | | | Upgrading IT infrastructure, such as high-speed broadband | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful | A little helpful | Helpful | Not helpful at all | Very helpful |
| ITA | 50-249 | ICT | 8 (26.7%) | 16 (53.3%) | 1 (3.3%) | 5 (16.7%) | 7 (23.3%) | 13 (43.3%) | 1 (3.3%) | 9 (30.0%) | 3 (10.0%) | 15 (50.0%) | 1 (3.3%) | 11 (36.7%) |
| | | MFT | 5 (16.7%) | 17 (56.7%) | 1 (3.3%) | 7 (23.3%) | 6 (20.0%) | 13 (43.3%) | 1 (3.3%) | 10 (33.3%) | 6 (20.0%) | 11 (36.7%) | 0 (0.0%) | 13 (43.3%) |
| | 250+ | ICT | 5 (16.7%) | 14 (46.7%) | 0 (0.0%) | 11 (36.7%) | 7 (23.3%) | 15 (50.0%) | 2 (6.7%) | 6 (20.0%) | 5 (16.7%) | 18 (60.0%) | 0 (0.0%) | 7 (23.3%) |
| | | MFT | 9 (30.0%) | 15 (50.0%) | 2 (6.7%) | 4 (13.3%) | 2 (6.7%) | 10 (33.3%) | 2 (6.7%) | 16 (53.3%) | 3 (10.0%) | 11 (36.7%) | 1 (3.3%) | 15 (50.0%) |
| JPN | 50-249 | ICT | 8 (26.7%) | 13 (43.3%) | 2 (6.7%) | 7 (23.3%) | 6 (20.0%) | 14 (46.7%) | 0 (0.0%) | 10 (33.3%) | 4 (13.3%) | 14 (46.7%) | 0 (0.0%) | 12 (40.0%) |
| | | MFT | 5 (16.7%) | 12 (40.0%) | 0 (0.0%) | 13 (43.3%) | 6 (20.0%) | 14 (46.7%) | 0 (0.0%) | 10 (33.3%) | 2 (6.7%) | 11 (36.7%) | 0 (0.0%) | 17 (56.7%) |
| | 250+ | ICT | 6 (20.0%) | 15 (50.0%) | 0 (0.0%) | 9 (30.0%) | 7 (23.3%) | 12 (40.0%) | 1 (3.3%) | 10 (33.3%) | 8 (26.7%) | 11 (36.7%) | 0 (0.0%) | 11 (36.7%) |
| | | MFT | 9 (30.0%) | 11 (36.7%) | 3 (10.0%) | 7 (23.3%) | 5 (16.7%) | 15 (50.0%) | 1 (3.3%) | 9 (30.0%) | 6 (20.0%) | 9 (30.0%) | 2 (6.7%) | 13 (43.3%) |
| USA | 50-249 | ICT | 4 (13.3%) | 8 (26.7%) | 4 (13.3%) | 14 (46.7%) | 8 (26.7%) | 13 (43.3%) | 2 (6.7%) | 7 (23.3%) | 9 (30.0%) | 10 (33.3%) | 5 (16.7%) | 6 (20.0%) |
| | | MFT | 11 (36.7%) | 13 (43.3%) | 1 (3.3%) | 5 (16.7%) | 6 (20.0%) | 13 (43.3%) | 1 (3.3%) | 10 (33.3%) | 6 (20.0%) | 12 (40.0%) | 1 (3.3%) | 11 (36.7%) |
| | 250+ | ICT | 8 (26.7%) | 15 (50.0%) | 1 (3.3%) | 6 (20.0%) | 8 (26.7%) | 12 (40.0%) | 1 (3.3%) | 9 (30.0%) | 4 (13.3%) | 14 (46.7%) | 3 (10.0%) | 9 (30.0%) |
| | | MFT | 13 (43.3%) | 6 (20.0%) | 3 (10.0%) | 8 (26.7%) | 5 (16.7%) | 18 (60.0%) | 1 (3.3%) | 6 (20.0%) | 5 (16.7%) | 11 (36.7%) | 3 (10.0%) | 11 (36.7%) |

Note: MFT = Manufacturing.

### Table E.20. Q16 - Some uses of AI that involve autonomous systems might be detrimental to clients, potentially exposing businesses to legal jeopardy. Would you favour regulation that helps to overcome such a problem by establishing clear accountability when AI is used?

| Country | Enterprise size | Sector | No | Yes |
|---|---|---|---|---|
| CAN | 50-249 | ICT | 4 (13.3%) | 26 (86.7%) |
| | | Manufacturing | 1 (3.3%) | 29 (96.7%) |
| | 250+ | ICT | 1 (3.3%) | 29 (96.7%) |
| | | Manufacturing | 5 (16.7%) | 25 (83.3%) |
| DEU | 50-249 | ICT | 6 (20.0%) | 24 (80.0%) |
| | | Manufacturing | 4 (13.3%) | 26 (86.7%) |
| | 250+ | ICT | 4 (13.3%) | 26 (86.7%) |
| | | Manufacturing | 10 (33.3%) | 20 (66.7%) |
| FRA | 50-249 | ICT | 2 (6.7%) | 28 (93.3%) |
| | | Manufacturing | 0 (0.0%) | 30 (100.0%) |
| | 250+ | ICT | 0 (0.0%) | 30 (100.0%) |
| | | Manufacturing | 7 (23.3%) | 23 (76.7%) |
| GBR | 50-249 | ICT | 1 (3.3%) | 29 (96.7%) |
| | | Manufacturing | 3 (10.0%) | 27 (90.0%) |
| | 250+ | ICT | 3 (10.0%) | 27 (90.0%) |

| Country | Enterprise size | Sector | No | Yes |
|---|---|---|---|---|
| | | Manufacturing | 4 (13.3%) | 26 (86.7%) |
| ITA | 50-249 | ICT | 4 (13.3%) | 26 (86.7%) |
| | | Manufacturing | 3 (10.0%) | 27 (90.0%) |
| | 250+ | ICT | 3 (10.0%) | 27 (90.0%) |
| | | Manufacturing | 2 (6.7%) | 28 (93.3%) |
| JPN | 50-249 | ICT | 2 (6.7%) | 28 (93.3%) |
| | | Manufacturing | 1 (3.3%) | 29 (96.7%) |
| | 250+ | ICT | 4 (13.3%) | 26 (86.7%) |
| | | Manufacturing | 2 (6.7%) | 28 (93.3%) |
| USA | 50-249 | ICT | 4 (13.3%) | 26 (86.7%) |
| | | Manufacturing | 12 (40.0%) | 18 (60.0%) |
| | 250+ | ICT | 3 (10.0%) | 27 (90.0%) |
| | | Manufacturing | 9 (30.0%) | 21 (70.0%) |

## Table E.21. Q17 - Are any of the following criteria important for your enterprise when developing or using AI applications?

| Country | Enterprise size | Sector | The protection of customer data and privacy | | | | Making our customers aware of how our AI system(s) are developed, trained and used | | | | Keeping a full record of our AI applications' predictions, recommendations or decisions | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Agree | Disagree | Strongly agree | Strongly disagree | Agree | Disagree | Strongly agree | Strongly disagree | Agree | Disagree | Strongly agree | Strongly disagree |
| CAN | 50-249 | ICT | 10 (33.3%) | 0 (0.0%) | 20 (66.7%) | 0 (0.0%) | 13 (43.3%) | 5 (16.7%) | 11 (36.7%) | 1 (3.3%) | 15 (50.0%) | 2 (6.7%) | 13 (43.3%) | 0 (0.0%) |
| | | MFT | 15 (50.0%) | 0 (0.0%) | 15 (50.0%) | 0 (0.0%) | 18 (60.0%) | 3 (10.0%) | 9 (30.0%) | 0 (0.0%) | 14 (46.7%) | 3 (10.0%) | 13 (43.3%) | 0 (0.0%) |
| | 250+ | ICT | 8 (26.7%) | 0 (0.0%) | 22 (73.3%) | 0 (0.0%) | 15 (50.0%) | 3 (10.0%) | 12 (40.0%) | 0 (0.0%) | 16 (53.3%) | 2 (6.7%) | 12 (40.0%) | 0 (0.0%) |
| | | MFT | 9 (30.0%) | 2 (6.7%) | 19 (63.3%) | 0 (0.0%) | 10 (33.3%) | 7 (23.3%) | 9 (30.0%) | 4 (13.3%) | 11 (36.7%) | 8 (26.7%) | 11 (36.7%) | 0 (0.0%) |
| DEU | 50-249 | ICT | 15 (50.0%) | 0 (0.0%) | 15 (50.0%) | 0 (0.0%) | 16 (53.3%) | 1 (3.3%) | 13 (43.3%) | 0 (0.0%) | 16 (53.3%) | 2 (6.7%) | 12 (40.0%) | 0 (0.0%) |
| | | MFT | 9 (30.0%) | 2 (6.7%) | 19 (63.3%) | 0 (0.0%) | 10 (33.3%) | 4 (13.3%) | 16 (53.3%) | 0 (0.0%) | 18 (60.0%) | 3 (10.0%) | 9 (30.0%) | 0 (0.0%) |
| | 250+ | ICT | 11 (36.7%) | 1 (3.3%) | 18 (60.0%) | 0 (0.0%) | 13 (43.3%) | 6 (20.0%) | 11 (36.7%) | 0 (0.0%) | 16 (53.3%) | 4 (13.3%) | 10 (33.3%) | 0 (0.0%) |
| | | MFT | 14 (46.7%) | 1 (3.3%) | 15 (50.0%) | 0 (0.0%) | 15 (50.0%) | 8 (26.7%) | 6 (20.0%) | 1 (3.3%) | 17 (56.7%) | 5 (16.7%) | 8 (26.7%) | 0 (0.0%) |
| FRA | 50-249 | ICT | 7 (23.3%) | 3 (10.0%) | 20 (66.7%) | 0 (0.0%) | 11 (36.7%) | 4 (13.3%) | 13 (43.3%) | 2 (6.7%) | 14 (46.7%) | 4 (13.3%) | 12 (40.0%) | 0 (0.0%) |
| | | MFT | 8 (26.7%) | 0 (0.0%) | 22 (73.3%) | 0 (0.0%) | 17 (56.7%) | 1 (3.3%) | 12 (40.0%) | 0 (0.0%) | 10 (33.3%) | 2 (6.7%) | 18 (60.0%) | 0 (0.0%) |
| | 250+ | ICT | 5 (16.7%) | 0 (0.0%) | 25 (83.3%) | 0 (0.0%) | 14 (46.7%) | 2 (6.7%) | 14 (46.7%) | 0 (0.0%) | 16 (53.3%) | 2 (6.7%) | 12 (40.0%) | 0 (0.0%) |
| | | MFT | 10 (33.3%) | 1 (3.3%) | 19 (63.3%) | 0 (0.0%) | 10 (33.3%) | 7 (23.3%) | 12 (40.0%) | 1 (3.3%) | 14 (46.7%) | 2 (6.7%) | 13 (43.3%) | 1 (3.3%) |
| GBR | 50-249 | ICT | 13 (43.3%) | 1 (3.3%) | 16 (53.3%) | 0 (0.0%) | 14 (46.7%) | 7 (23.3%) | 9 (30.0%) | 0 (0.0%) | 15 (50.0%) | 5 (16.7%) | 10 (33.3%) | 0 (0.0%) |
| | | MFT | 7 (23.3%) | 0 (0.0%) | 23 (76.7%) | 0 (0.0%) | 18 (60.0%) | 0 (0.0%) | 11 (36.7%) | 1 (3.3%) | 11 (36.7%) | 2 (6.7%) | 17 (56.7%) | 0 (0.0%) |
| | 250+ | ICT | 5 (16.7%) | 1 (3.3%) | 24 (80.0%) | 0 (0.0%) | 14 (46.7%) | 6 (20.0%) | 10 (33.3%) | 0 (0.0%) | 14 (46.7%) | 2 (6.7%) | 14 (46.7%) | 0 (0.0%) |

| Country | Enterprise size | Sector | The protection of customer data and privacy | | | | Making our customers aware of how our AI system(s) are developed, trained and used | | | | Keeping a full record of our AI applications' predictions, recommendations or decisions | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Agree | Disagree | Strongly agree | Strongly disagree | Agree | Disagree | Strongly agree | Strongly disagree | Agree | Disagree | Strongly agree | Strongly disagree |
| | | MFT | 14 (46.7%) | 0 (0.0%) | 16 (53.3%) | 0 (0.0%) | 10 (33.3%) | 8 (26.7%) | 12 (40.0%) | 0 (0.0%) | 17 (56.7%) | 1 (3.3%) | 12 (40.0%) | 0 (0.0%) |
| ITA | 50-249 | ICT | 18 (60.0%) | 2 (6.7%) | 10 (33.3%) | 0 (0.0%) | 10 (33.3%) | 6 (20.0%) | 14 (46.7%) | 0 (0.0%) | 15 (50.0%) | 6 (20.0%) | 9 (30.0%) | 0 (0.0%) |
| | | MFT | 13 (43.3%) | 1 (3.3%) | 16 (53.3%) | 0 (0.0%) | 14 (46.7%) | 4 (13.3%) | 12 (40.0%) | 0 (0.0%) | 13 (43.3%) | 5 (16.7%) | 12 (40.0%) | 0 (0.0%) |
| | 250+ | ICT | 7 (23.3%) | 1 (3.3%) | 22 (73.3%) | 0 (0.0%) | 17 (56.7%) | 5 (16.7%) | 8 (26.7%) | 0 (0.0%) | 14 (46.7%) | 4 (13.3%) | 12 (40.0%) | 0 (0.0%) |
| | | MFT | 11 (36.7%) | 0 (0.0%) | 19 (63.3%) | 0 (0.0%) | 10 (33.3%) | 8 (26.7%) | 12 (40.0%) | 0 (0.0%) | 14 (46.7%) | 4 (13.3%) | 12 (40.0%) | 0 (0.0%) |
| JPN | 50-249 | ICT | 7 (23.3%) | 3 (10.0%) | 20 (66.7%) | 0 (0.0%) | 9 (30.0%) | 6 (20.0%) | 15 (50.0%) | 0 (0.0%) | 24 (80.0%) | 0 (0.0%) | 6 (20.0%) | 0 (0.0%) |
| | | MFT | 5 (16.7%) | 1 (3.3%) | 24 (80.0%) | 0 (0.0%) | 17 (56.7%) | 2 (6.7%) | 11 (36.7%) | 0 (0.0%) | 15 (50.0%) | 2 (6.7%) | 13 (43.3%) | 0 (0.0%) |
| | 250+ | ICT | 11 (36.7%) | 1 (3.3%) | 18 (60.0%) | 0 (0.0%) | 15 (50.0%) | 7 (23.3%) | 7 (23.3%) | 1 (3.3%) | 17 (56.7%) | 3 (10.0%) | 10 (33.3%) | 0 (0.0%) |
| | | MFT | 12 (40.0%) | 0 (0.0%) | 18 (60.0%) | 0 (0.0%) | 21 (70.0%) | 3 (10.0%) | 6 (20.0%) | 0 (0.0%) | 17 (56.7%) | 2 (6.7%) | 11 (36.7%) | 0 (0.0%) |
| USA | 50-249 | ICT | 6 (20.0%) | 0 (0.0%) | 24 (80.0%) | 0 (0.0%) | 12 (40.0%) | 6 (20.0%) | 10 (33.3%) | 2 (6.7%) | 14 (46.7%) | 3 (10.0%) | 10 (33.3%) | 3 (10.0%) |
| | | MFT | 12 (40.0%) | 0 (0.0%) | 18 (60.0%) | 0 (0.0%) | 11 (36.7%) | 11 (36.7%) | 7 (23.3%) | 1 (3.3%) | 17 (56.7%) | 5 (16.7%) | 8 (26.7%) | 0 (0.0%) |
| | 250+ | ICT | 7 (23.3%) | 0 (0.0%) | 23 (76.7%) | 0 (0.0%) | 17 (56.7%) | 5 (16.7%) | 8 (26.7%) | 0 (0.0%) | 14 (46.7%) | 2 (6.7%) | 14 (46.7%) | 0 (0.0%) |
| | | MFT | 6 (20.0%) | 0 (0.0%) | 24 (80.0%) | 0 (0.0%) | 14 (46.7%) | 6 (20.0%) | 8 (26.7%) | 2 (6.7%) | 19 (63.3%) | 1 (3.3%) | 10 (33.3%) | 0 (0.0%) |

Note: MFT = Manufacturing.

## Table E.22. Q18 - Are you aware that some regulators are considering the following requirements to increase oversight of artificial intelligence applications?

| Country | Enterprise size | Sector | Certification of the safety of AI systems | | Notification for customers when decision making is automated | |
|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes |
| CAN | 50-249 | ICT | 5 (16.7%) | 25 (83.3%) | 11 (36.7%) | 19 (63.3%) |
| | | Manufacturing | 3 (10.0%) | 27 (90.0%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 8 (26.7%) | 22 (73.3%) | 10 (33.3%) | 20 (66.7%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 18 (60.0%) | 12 (40.0%) |
| DEU | 50-249 | ICT | 5 (16.7%) | 25 (83.3%) | 11 (36.7%) | 19 (63.3%) |
| | | Manufacturing | 5 (16.7%) | 25 (83.3%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 6 (20.0%) | 24 (80.0%) | 9 (30.0%) | 21 (70.0%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 13 (43.3%) | 17 (56.7%) |
| FRA | 50-249 | ICT | 1 (3.3%) | 29 (96.7%) | 11 (36.7%) | 19 (63.3%) |
| | | Manufacturing | 1 (3.3%) | 29 (96.7%) | 4 (13.3%) | 26 (86.7%) |
| | 250+ | ICT | 4 (13.3%) | 26 (86.7%) | 6 (20.0%) | 24 (80.0%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 10 (33.3%) | 20 (66.7%) |
| GBR | 50-249 | ICT | 6 (20.0%) | 24 (80.0%) | 11 (36.7%) | 19 (63.3%) |

| Country | Enterprise size | Sector | Certification of the safety of AI systems | | Notification for customers when decision making is automated | |
|---|---|---|---|---|---|---|
| | | | No | Yes | No | Yes |
| | | Manufacturing | 4 (13.3%) | 26 (86.7%) | 8 (26.7%) | 22 (73.3%) |
| | 250+ | ICT | 10 (33.3%) | 20 (66.7%) | 9 (30.0%) | 21 (70.0%) |
| | | Manufacturing | 9 (30.0%) | 21 (70.0%) | 15 (50.0%) | 15 (50.0%) |
| ITA | 50-249 | ICT | 5 (16.7%) | 25 (83.3%) | 10 (33.3%) | 20 (66.7%) |
| | | Manufacturing | 8 (26.7%) | 22 (73.3%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 7 (23.3%) | 23 (76.7%) | 7 (23.3%) | 23 (76.7%) |
| | | Manufacturing | 10 (33.3%) | 20 (66.7%) | 11 (36.7%) | 19 (63.3%) |
| JPN | 50-249 | ICT | 2 (6.7%) | 28 (93.3%) | 9 (30.0%) | 21 (70.0%) |
| | | Manufacturing | 3 (10.0%) | 27 (90.0%) | 10 (33.3%) | 20 (66.7%) |
| | 250+ | ICT | 3 (10.0%) | 27 (90.0%) | 14 (46.7%) | 16 (53.3%) |
| | | Manufacturing | 4 (13.3%) | 26 (86.7%) | 12 (40.0%) | 18 (60.0%) |
| USA | 50-249 | ICT | 11 (36.7%) | 19 (63.3%) | 12 (40.0%) | 18 (60.0%) |
| | | Manufacturing | 5 (16.7%) | 25 (83.3%) | 17 (56.7%) | 13 (43.3%) |
| | 250+ | ICT | 8 (26.7%) | 22 (73.3%) | 10 (33.3%) | 20 (66.7%) |
| | | Manufacturing | 17 (56.7%) | 13 (43.3%) | 17 (56.7%) | 13 (43.3%) |

## Table E.23. Q19 - Approximately what percentage of your enterprise's total spending (internal and external) on R&D in 2021 was related to artificial intelligence?

If not available, please answer based on 2020 spending

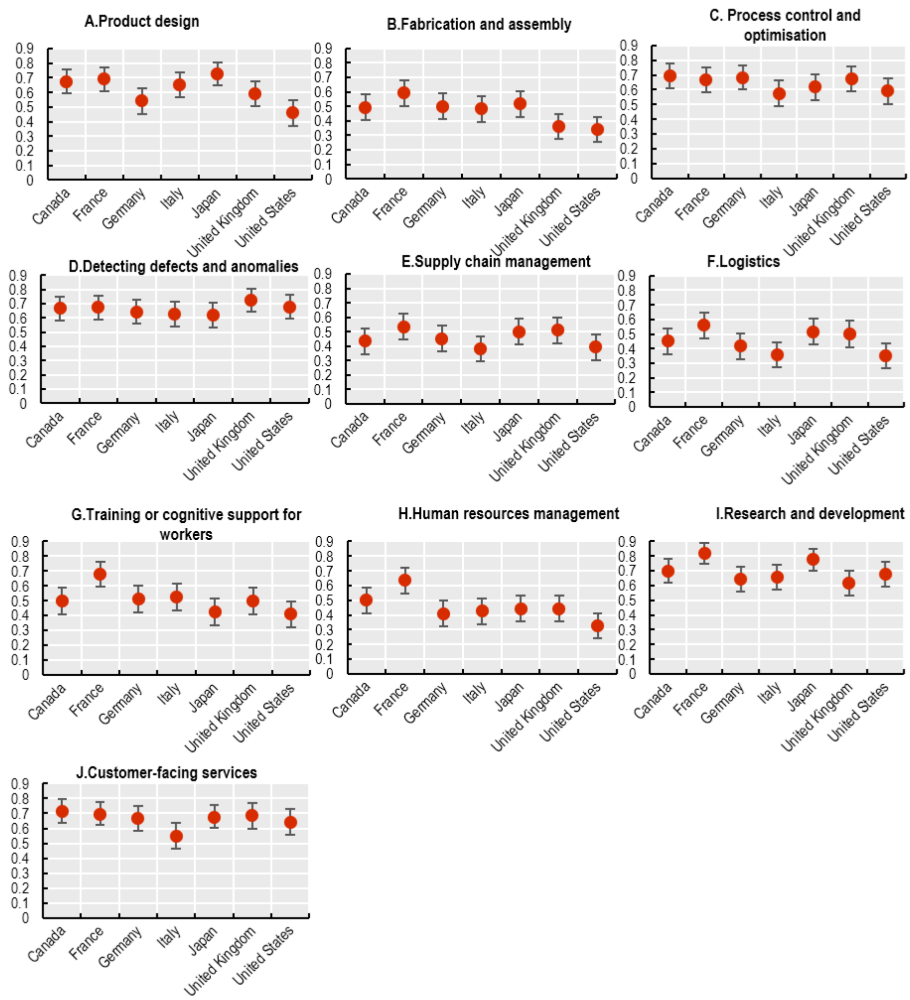
| Country | Enterprise size | Sector | 0% | Between 1% and 10% | Between 11% and 30% | Cannot discuss | More than 30% | The enterprise does not spend on R&D |
|---|---|---|---|---|---|---|---|---|
| CAN | 50-249 | ICT | 0 (0.0%) | 14 (46.7%) | 12 (40.0%) | 0 (0.0%) | 4 (13.3%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 15 (50.0%) | 12 (40.0%) | 0 (0.0%) | 3 (10.0%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 16 (53.3%) | 11 (36.7%) | 1 (3.3%) | 1 (3.3%) | 1 (3.3%) |
| | | Manufacturing | 0 (0.0%) | 21 (70.0%) | 8 (26.7%) | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) |
| DEU | 50-249 | ICT | 0 (0.0%) | 8 (26.7%) | 15 (50.0%) | 0 (0.0%) | 7 (23.3%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 19 (63.3%) | 9 (30.0%) | 0 (0.0%) | 2 (6.7%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 11 (36.7%) | 15 (50.0%) | 0 (0.0%) | 4 (13.3%) | 0 (0.0%) |
| | | Manufacturing | 2 (6.7%) | 22 (73.3%) | 3 (10.0%) | 2 (6.7%) | 1 (3.3%) | 0 (0.0%) |
| FRA | 50-249 | ICT | 0 (0.0%) | 7 (23.3%) | 16 (53.3%) | 0 (0.0%) | 7 (23.3%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 9 (30.0%) | 15 (50.0%) | 0 (0.0%) | 6 (20.0%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 13 (43.3%) | 14 (46.7%) | 2 (6.7%) | 1 (3.3%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 16 (53.3%) | 11 (36.7%) | 3 (10.0%) | 0 (0.0%) | 0 (0.0%) |
| GBR | 50-249 | ICT | 0 (0.0%) | 18 (60.0%) | 10 (33.3%) | 0 (0.0%) | 2 (6.7%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 16 (53.3%) | 6 (20.0%) | 1 (3.3%) | 7 (23.3%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 12 (40.0%) | 12 (40.0%) | 1 (3.3%) | 2 (6.7%) | 3 (10.0%) |
| | | Manufacturing | 1 (3.3%) | 20 (66.7%) | 6 (20.0%) | 2 (6.7%) | 1 (3.3%) | 0 (0.0%) |
| ITA | 50-249 | ICT | 0 (0.0%) | 15 (50.0%) | 14 (46.7%) | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 19 (63.3%) | 10 (33.3%) | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 15 (50.0%) | 13 (43.3%) | 0 (0.0%) | 2 (6.7%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 23 (76.7%) | 6 (20.0%) | 1 (3.3%) | 0 (0.0%) | 0 (0.0%) |
| JPN | 50-249 | ICT | 0 (0.0%) | 9 (30.0%) | 16 (53.3%) | 0 (0.0%) | 5 (16.7%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 11 (36.7%) | 18 (60.0%) | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 17 (56.7%) | 12 (40.0%) | 0 (0.0%) | 1 (3.3%) | 0 (0.0%) |

| Country | Enterprise size | Sector | 0% | Between 1% and 10% | Between 11% and 30% | Cannot discuss | More than 30% | The enterprise does not spend on R&D |
|---|---|---|---|---|---|---|---|---|
| | | Manufacturing | 0 (0.0%) | 15 (50.0%) | 13 (43.3%) | 1 (3.3%) | 0 (0.0%) | 1 (3.3%) |
| USA | 50-249 | ICT | 1 (3.3%) | 16 (53.3%) | 8 (26.7%) | 0 (0.0%) | 5 (16.7%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 14 (46.7%) | 13 (43.3%) | 1 (3.3%) | 2 (6.7%) | 0 (0.0%) |
| | 250+ | ICT | 0 (0.0%) | 19 (63.3%) | 5 (16.7%) | 4 (13.3%) | 2 (6.7%) | 0 (0.0%) |
| | | Manufacturing | 0 (0.0%) | 19 (63.3%) | 6 (20.0%) | 2 (6.7%) | 2 (6.7%) | 1 (3.3%) |

# Annex F. Predictive margins of AI use, by application and country

### Figure F.1. Predictive margins of AI use in 840 enterprises, by application and country, 2022-23

95% confidence intervals




Note: The figure depicts the predicted probability of using AI in the applications indicated in the figure heading. They are based on probit regressions controlling for enterprise size and country fixed effects. The applications included are those that produced a statistically significant overall fitness (Prob > chi2 = 0.01 or better), which means that the variables included jointly explain the probability of adopting the AI application well enough to pass standard statistical thresholds.

Source: OECD (2022-23[1]), *OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

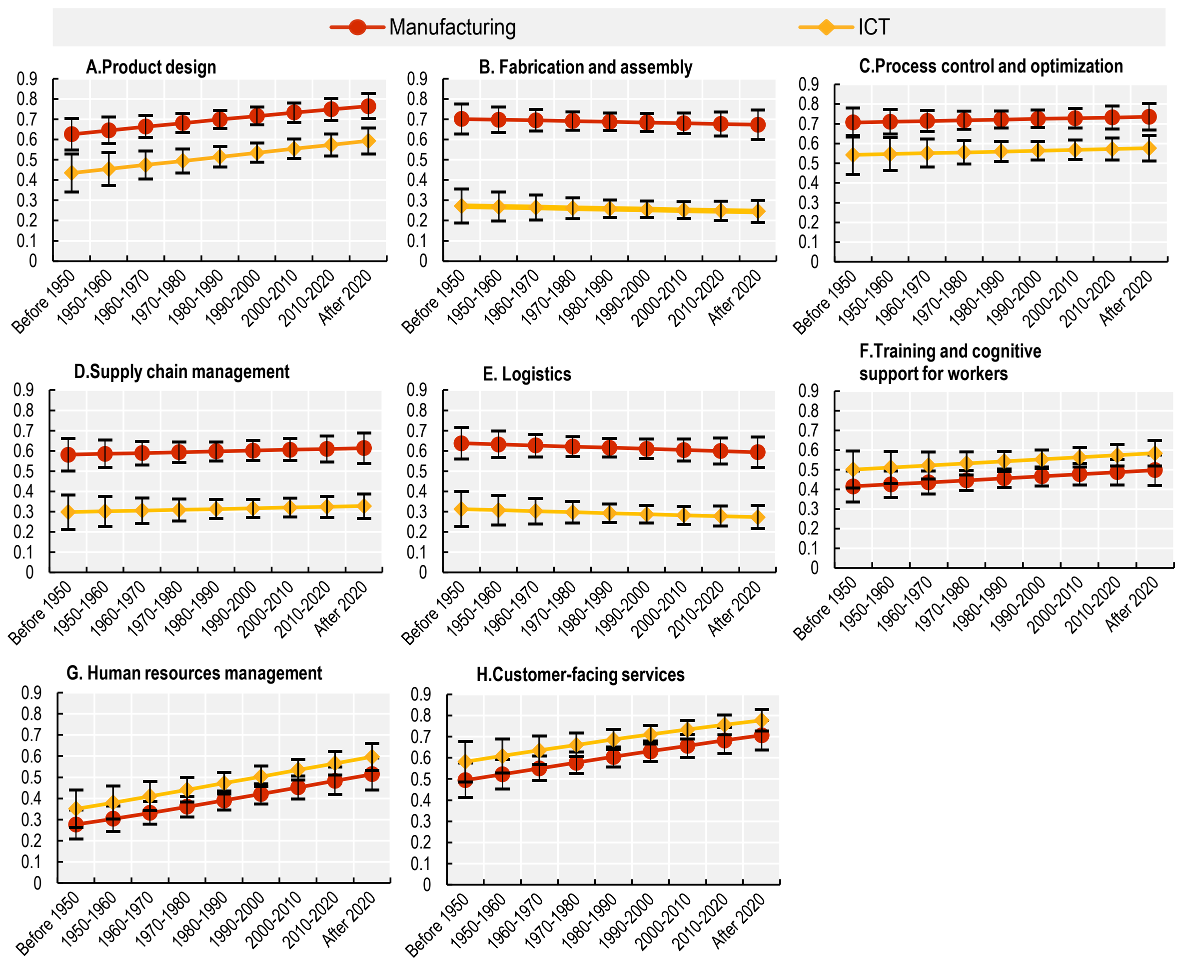
## References

OECD (2022-23), *OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*. [1]

# Annex G. Predictive margins of AI use by application, broad industry and enterprise age

### Figure G.1. Predictive margins of AI use in 840 enterprises across G7 countries, by application, broad industry and enterprise age (by decade of founding)

95% confidence intervals




Note: The probit regressions use country fixed effects. The horizontal axis shows the age of the enterprises. The oldest enterprises are situated to the left. Each point represents a decade.
Source: OECD (2022-23[1]), *OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*.

## References


OECD (2022-23), *OECD/BCG/INSEAD Survey of AI-Adopting Enterprises*. [1]

# Annex H. Correlations between AI intensity and the perceived helpfulness of selected public sector services

### Table H.1. Correlations between AI intensity and how helpful 840 enterprises across G7 countries find selected public sector services, 2022-23

Scores take values from 1 (very helpful) to 4 (not helpful at all)

| | Information or advice on business use case | Information or advice on the expected rate of return on AI investment | Information on available and reliable AI vendors | Information on available and reliable sources of private-sector advice | Certification or accreditation schemes for AI providers | Information on current or forthcoming regulation |
|---|---|---|---|---|---|---|
| Number of AI uses | -0.098*** | -0.036** | -0.026* | -0.043*** | -0.055*** | -0.056*** |
| | (-0.01) | (-0.01) | (-0.01) | (-0.01) | (-0.01) | (-0.01) |
| Number of AI obstacles | -0.054** | -0.054** | -0.035 | -0.056** | -0.062** | -0.039* |
| | (-0.02) | (-0.02) | (-0.02) | (-0.02) | (-0.02) | (-0.02) |
| Size | 0.098 | -0.02 | 0.034 | 0.102 | 0.121* | 0.008 |
| | (0.05) | (0.06) | (0.06) | (0.05) | (0.06) | (0.06) |
| Age | 0.02 | -0.002 | -0.011 | -0.009 | 0.016 | -0.006 |
| | (-0.01) | (-0.01) | (-0.01) | (-0.01) | (0.01) | (-0.01) |
| $R^2$ | 0.141 | 0.035 | 0.041 | 0.069 | 0.081 | 0.054 |
| Number of observations | 836 | 836 | 836 | 836 | 836 | 836 |
| Memo: Average score | 1.79 | 1.85 | 1.82 | 1.89 | 1.97 | 1.79 |

Note: The table presents the coefficients of OLS regressions for each service. Robust standard errors are in parentheses, where ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. All regressions are run with country fixed effects. The industry and country dummies are mostly statistically insignificant, suggesting that there is little to no systematic variation across countries and industries. The memos at the foot of the table show the average score on each item in the total sample of active AI users.

## Table H.2. Correlations between AI intensity and the score on how helpful 840 enterprises across G7 countries find selected public initiatives, 2022-23

Scores take values from 1 (very helpful) to 4 (not helpful at all)

| | Investing in education in fields related to AI | Investing in retraining for employees who work with AI | Improving understanding of AI among government officials | Gathering and publishing administrative public databases | Promoting a competitive AI vendor market |
|---|---|---|---|---|---|
| Number of AI uses | -0.078*** | -0.014 | -0.056*** | -0.079*** | -0.077*** |
| | (-0.01) | (-0.01) | (-0.01) | (-0.01) | (-0.01) |
| Number of AI obstacles | 0.007 | -0.026 | -0.061** | -0.059** | -0.045* |
| | (0.02) | (-0.02) | (-0.02) | (-0.02) | (-0.02) |
| Size | 0.013 | 0.154** | 0.054 | 0.03 | 0.032 |
| | (0.06) | (0.05) | (0.06) | (0.06) | (0.06) |
| Age | -0.016 | 0.022 | -0.009 | -0.021 | -0.009 |
| | (-0.01) | (0.01) | (-0.01) | (-0.01) | (-0.01) |
| $R^2$ | 0.101 | 0.03 | 0.063 | 0.091 | 0.073 |
| Number of observations | 836 | 836 | 836 | 836 | 836 |
| Memo: Average score | 1.83 | 1.71 | 1.97 | 1.99 | 1.93 |

Note: The table presents the coefficients of OLS regressions for each service. Robust standard errors are in parentheses, where ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. All regressions are run with country fixed effects. The industry and country dummies are mostly statistically insignificant, suggesting that there is little to no systematic variation across countries and industries. The memos at the foot of the table show the average score on each item in the total sample of active AI users.

# Annex I. Interview questions

## Table A I.1. Part 1: About your institution

| Questions |
|---|
| Could you describe how your institution supports the development of AI applications? |
| Roughly how many SMEs do you work with per year – if it is possible to say? |
| Do you have a specific strategy to find and reach out to the population of enterprises most likely to adopt AI? How does that work? |

## Table A I.2. Part 2: Barriers to AI adoption

| Questions |
|---|
| Uptake of AI in manufacturing, ICT and other sectors – in core business processes – is actually quite low. Do you think that SMEs, in general, are aware of the potential uses of AI in their sector? And what do you or your colleagues see as the key barriers to AI adoption today? |
| Do you do any form of systematic evidence gathering (like survey work) to assess the extent of these barriers among businesses? |
| What do you think is the most underestimated difficulty when initially trying to adopt AI? |

## Table A I.3. Part 3: Forms of support

| Questions |
|---|
| In your experience, what types of advice and support are most effective for enterprises trying to adopt AI? |
| One problem we find is that it can be difficult for firms to calculate the return on investments in AI. Do you agree, and do you work on aiding firms in this connection? If so, kindly tell us about your approach. |
| Is there something different with respect to supporting AI adoption that you plan or would like to implement in future? |
| If budget were not a limit, what would you want to do to facilitate AI uptake in firms, particularly SMEs? |

# The Adoption of Artificial Intelligence in Firms

## New Evidence for Policymaking

Artificial intelligence (AI) could help to address sluggish productivity growth in OECD countries. This book provides evidence for policymakers, business leaders, and researchers to help understand the adoption of AI in enterprises and the policies needed to enable this. The core analysis draws on a new policy-oriented survey of AI in enterprises across the Group of Seven (G7) countries and Brazil, complemented by interviews with business representatives. The book offers a comprehensive examination of barriers to the use of AI and examines actionable solutions, including in the areas of training and education, qualification frameworks, public-private research partnerships, and public data. Also examined is the work of public institutions that seek to facilitate the diffusion of digital technologies, including AI. Further, this book highlights the need for better policy evaluation, greater international comparability in surveys of AI, and studies of generative AI in business (widespread interest in which began after this survey).

PRINT ISBN 978-92-64-80375-6
PDF ISBN 978-92-64-57040-5

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