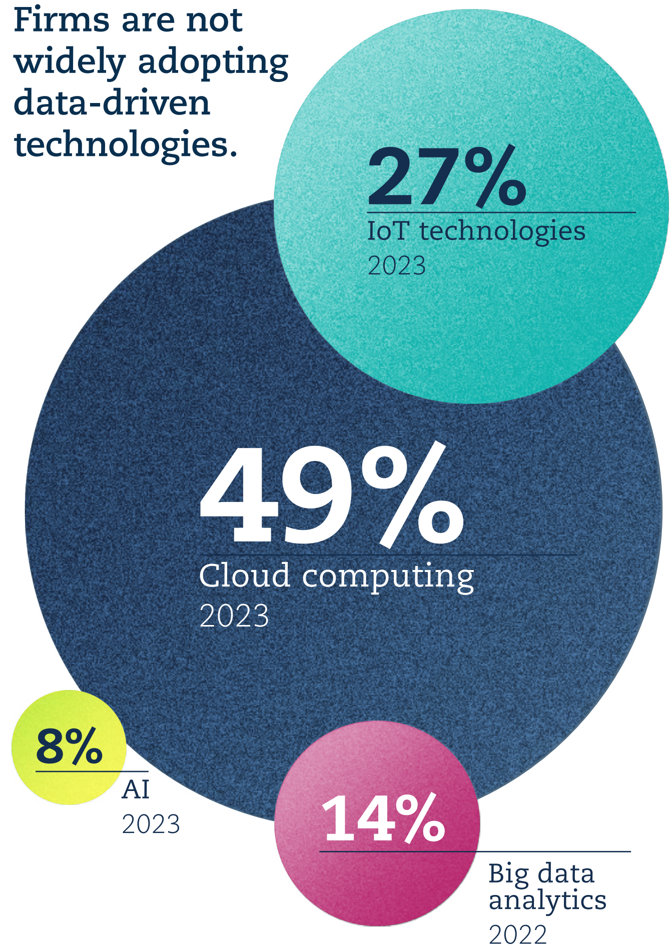
Chapter 3

Digital technology diffusion and data

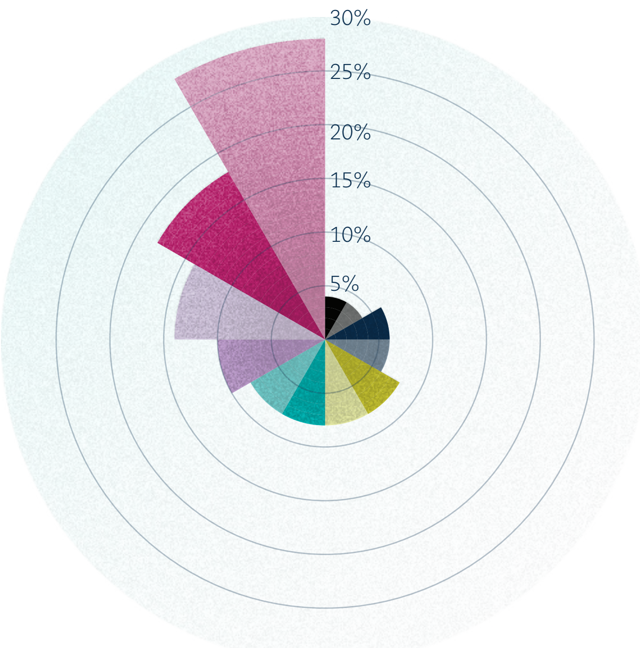
Digital technologies and data have dramatically changed the way people live and work, how and in which markets firms operate, and the ways in which governments interact with citizens. This brings many opportunities, as well as new challenges. As governments and the private sector increasingly shift from offline to online service provision, access and effective use of digital technologies become critical for equal opportunity and inclusion. Technologies such as cloud computing and Internet of Things (IoT) have diffused rapidly in recent years. However, productivity growth remains slow, including in digital-intensive sectors. Adoption of data-dependent technologies also remains low. This chapter considers both issues in turn before highlighting policy actions to make digital technologies and data more inclusive and productive.

Technology is spreading fast, but gaps remain

Firms are not widely adopting data-driven technologies.



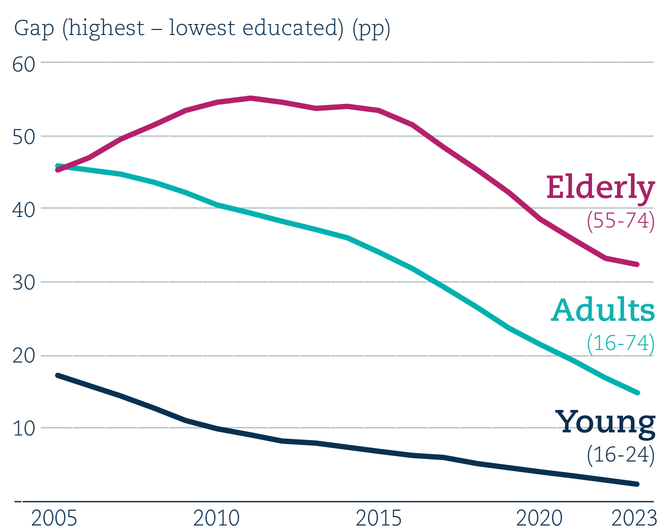
28% of ICT firms used AI in 2023 in the OECD, higher than any other sector.



- 4% Construction
- 4% Accommodation and food services
- 6% Retail trade
- 6% Transportation and storage
- 8% Administration and support
- 8% Manufacturing
- 8% Electricity, gas, water and waste mgt.
- 8% Wholesale trade
- 10% Real estate
- 15% Professional and technical activities
- 18% Finance and insurance
- 28% Information and communications tech.

Highly educated adults are 15 percentage points (pp) more likely to use the Internet.

Gap in Internet usage between high and low levels of education, by age group



Key findings

Access to online services and the ability to use them effectively are critical for equal opportunity and inclusion

- Divides in Internet use are pronounced by age, education and income. Younger and more educated Internet users engage in a wider range of online activities.
- Those with the requisite skills are typically in a better position to use digital technologies to their advantage, something highlighted during the COVID-19 pandemic.
- Uptake of specific online services increased during the COVID-19 pandemic, chiefly among those already on line, raising the expectation that this trend may continue. Moreover, two or three days of teleworking per week are now common among those with jobs that allow for it.
- Not all effects of the pandemic may be long lasting, as the share of retail e-commerce is converging to pre-pandemic trends.

Data-dependent technologies are diffusing at a slow pace

- While the adoption of cloud computing and IoT technologies is strong across the OECD, adoption of big data analytics and artificial intelligence (AI) remains low.
- AI adoption is concentrated in the information and communication technology (ICT) sector, where an average of 28% of ICT firms used AI in 2023 in the OECD, higher than any other sector.
- Firm size is a more important predictor of adoption for data-dependent technologies than for cloud computing and IoT technologies.
- While the number of IoT devices has been growing rapidly, it has slowed in the wake of the semiconductor shortage.

Policies should aim to boost equitable uptake of online services, technology diffusion and the potential of data

- To boost equitable uptake of online services, governments should lead by example, providing user-centric, inclusive online services. They should invest in people's skills, while supporting those most at risk of being left behind.
- Technology diffusion can be accelerated by creating a level playing field among firms for access to key inputs, including data.

How quickly are individuals, consumers and firms adopting digital technologies? Who is benefiting from them and who is at risk of being left behind? This chapter first looks at Internet adoption and use of online services by individuals, highlighting differences across socio-demographic and socio-economic groups and the impact of COVID-19. It then looks at the diffusion of digital technologies across firms – with a focus on data-dependent technologies such as big data analytics and AI – before turning to policy implications.

The ability to use the Internet effectively is key for equal opportunity and inclusion

Digital technologies provide opportunities to improve the lives and well-being of people. Yet there have also been three long-standing concerns, notably about their impact on equal opportunities and inclusion. These concerns are highlighted below.

First, to the extent that digital technologies offer sizeable benefits to those who know how to use them effectively, they might deepen long-standing divides. Online education programmes, for instance, offer the opportunity to access quality educational content at low cost and in a flexible way. However, if skills or formal education are a prerequisite to making effective use of these programmes, they offer fewer benefits to those that are already at a disadvantage (OECD, 2020[1]).

Second, ever more services – from written correspondence to shopping to banking and interactions with the government – are offered on line and ever more people are using them. As a result, the per-interaction cost of providing these services off line increases. Consequently, the physical counterparts of online services and their infrastructure – brick-and-mortar post offices, banks, bookstores and so on – are in decline across much of the OECD.[1] The number of bank branches per 10 000 inhabitants in Germany, for example, decreased from more than 7.0 in 1995 to less than 2.5 by 2021. Over the same period, the number of bookstores in the United States decreased from 5.0 per 100 000 inhabitants to 1.7.

This “dematerialisation of services” threatens to leave the unconnected and those that lack the resources to use online services with less choice and higher transaction costs (Défenseur des Droits, 2022[2]).

Finally, as social interactions and cultural activities are increasingly moving on line, access to digital technologies and the ability to use them effectively are becoming key for social inclusion. There are many dimensions of digital exclusion: politicians addressing the public via social media; families and friends congregating in chat groups; and people unable to take part in real-life conversations about online-only cultural phenomena, to name a few. The more social interactions and cultural phenomena move on line, the more important universal access and use become.

The long-standing trends described above accelerated with the onset of the COVID-19 pandemic. At its height, lockdowns shifted everything from office work to school classes and doctor appointments on line. Those that lacked quality access or the requisite skills to use digital technologies were at a severe disadvantage. Those in occupations more suitable to teleworking – typically occupations that require higher levels of educational attainment – were more likely to continue working (Dey et al., 2021[3]). Further, online retail spending increased more in economies with higher pre-pandemic e-commerce shares, exacerbating the digital divide across countries (Cavallo, Mishra and Spilimbergo, 2022[4]).

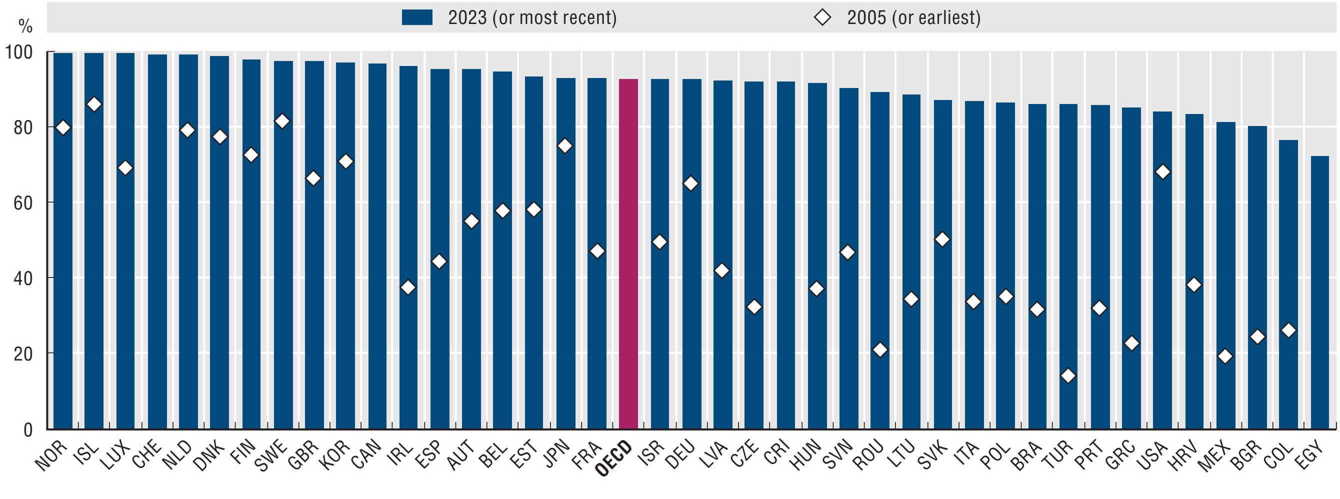
The incidence and frequency of Internet use have increased, but gaps remain

The incidence and frequency of Internet use have increased rapidly across OECD countries. Among adults aged 16-74, more than nine out of ten (93%) – or 945 million people – used the Internet at least once in the past 12 months.[2] More than four in five (87%) – or 888 million people – used the Internet daily or almost every day. By comparison, the rates were only one in two (52%) and one in three (32%) in 2005, respectively.

In ten OECD countries – Denmark, Finland, Iceland, Korea, Luxembourg, the Netherlands, Norway, Sweden, Switzerland and the United Kingdom – more than 97% of the population used the Internet over the last three months (Figure 3.1). By contrast, more than 15% of the adult population had not used the Internet in the past three months in Colombia, Greece, Mexico and the United States. However, countries that had lower usage rates in the past often have seen the largest increases. In Türkiye, for instance, only 7% of the population used the Internet daily in 2005, but 82% did by 2023.

Figure 3.1. Internet adoption has increased

Internet use at least once during the last three months among adults (aged 16-74), 2005 (or earliest) and 2023 (or most recent)



Note: See endnote 3.

Source: Authors’ elaboration based on data from OECD (2023[5]).

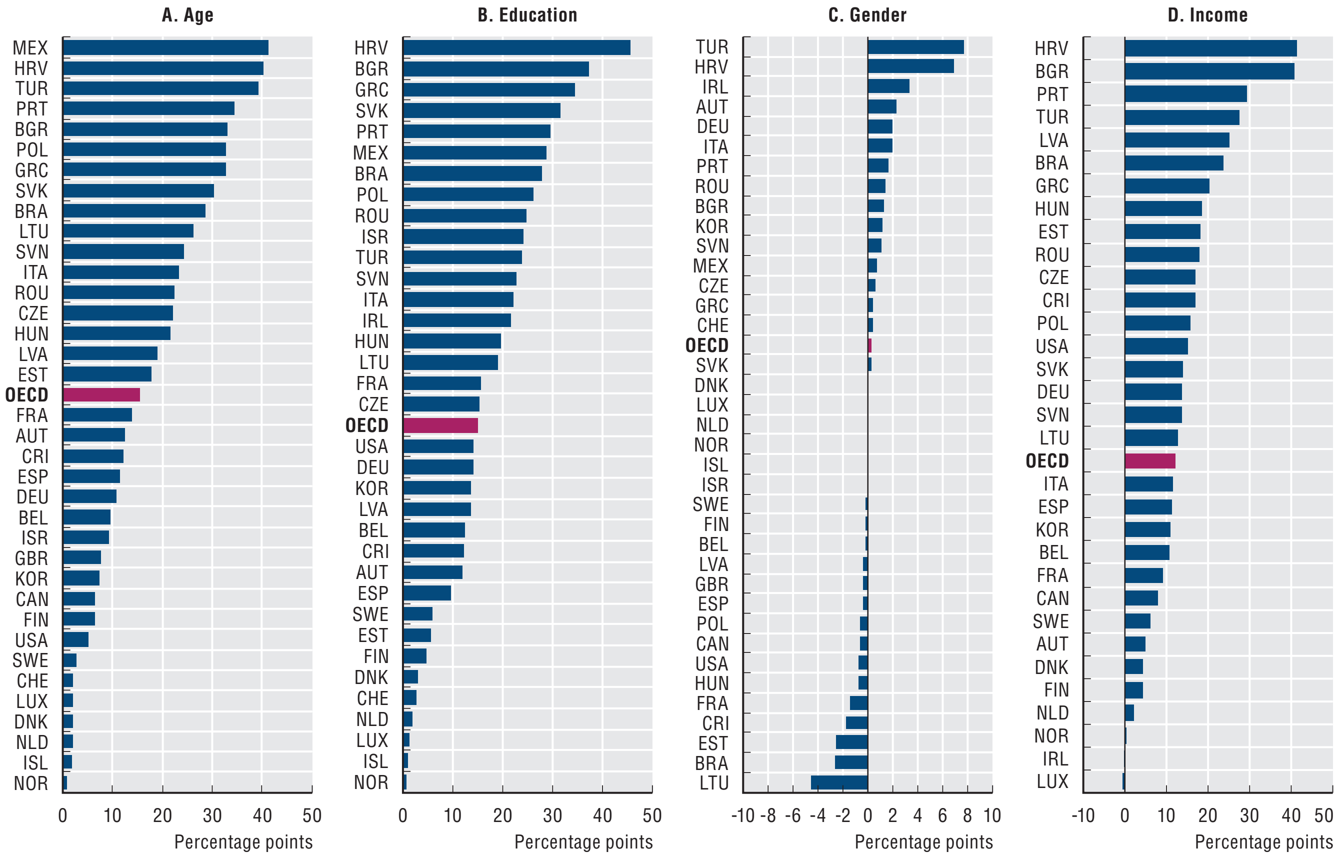
StatLink https://stat.link/803gwr

Internet adoption rates have been converging within OECD countries. However, a significant digital divide remains in relation to the rest of the world, where more than 80% of the global population lives. Only half of the population of today’s low- and middle-income countries is on line (ITU, 2022[6]). Across the population of the 28 low-income countries, only one in five used the Internet in the last three months.

Figure 3.2 shows gaps in Internet use between different socio-economic and socio-demographic groups, where gaps are defined as the difference in uptake rates by age, education, gender and income quintiles.[4] Divides in Internet use are pronounced between age groups and between individuals with different levels of educational attainment. On average, the young (ages 16-24) are 15 percentage points more likely to have used the Internet than the elderly (ages 55-74). Meanwhile, those with high levels of educational attainment are 15 percentage points more likely to use the Internet than those with low levels. Differences by gender are less pronounced. In fact, women are more likely to use the Internet in just over one-third of the countries for which data are available. Finally, the difference between those in the fifth quintile of the household income distribution and those in the first quintile is 12 percentage points on average.

Figure 3.2. Divides in Internet use are pronounced by age, education and income

Differences in the share of adults using the Internet at least once over the last three months, 2023 (or most recent)



Note: See endnotes 4 and 5.

Source: Authors' elaboration based on data from OECD (2023[5]).

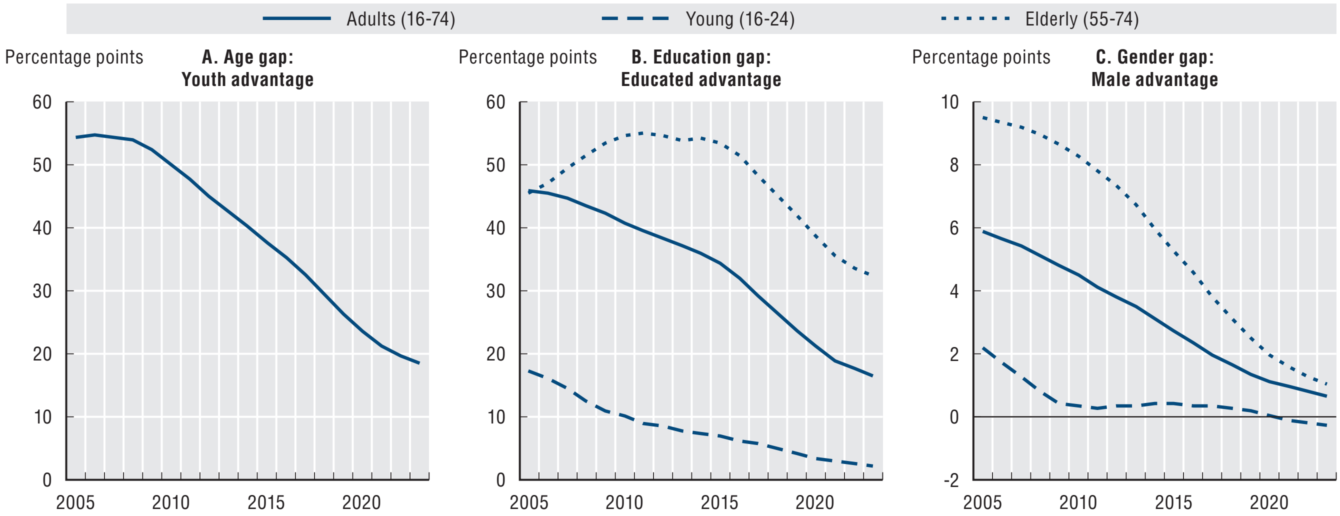
StatLink https://stat.link/105a9o

These findings are also in line with other evidence. A 2021 survey found that only 7% of adults in the United States are non-adopters, but that the share rises to 25% for adults aged 65 and older (Perrin and Atske, 2021[7]). Educational attainment and household income were also found to be linked to the likelihood of being on line. On the other hand, there were no statistically significant differences in Internet use by gender, race and ethnicity, or community type.

Figure 3.3 depicts the evolution of average gaps in Internet use (at least once in the last three months) across all OECD countries for which data are available. The average age gap and the average education gap have narrowed at a rate of about 3 percentage points per year since 2010. The average gender gap in Internet use, already much narrower than in the past, is also closing, albeit at a slower pace. The second and third panels of Figure 3.3 plot trends in the average gender and education gaps by age group. A gender gap favouring men is still discernible among the elderly whereas on average there has been no significant gender gap among the young since about 2010. Similarly, education gaps among the young are approaching zero on average, although progress has slowed in recent years. After peaking at around 55 percentage points during the first half of the last decade, the average education gap among the elderly is also narrowing but remains large at about 32 percentage points.[6]

Figure 3.3. Gaps in Internet use are narrowing but remain pronounced among the elderly

Average gaps across OECD countries, 2005-23



Notes: Estimates based on a local polynomial with a bandwidth of unity. See also endnote 4.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/uzcyvg

As divides across key dimensions tend to increase in age, they can be expected to narrow. How long will it take? The finding reported above suggests that age gaps in Internet use are closing at a rate of about 3 percentage points per year. This implies the average gap across countries may be closed by the end of the decade. However, this finding may be misleading as the data only cover those up to age 74. The population share of those 75 and older ranges from about 3% in Colombia, Mexico and Türkiye to more than 12% in Italy and Japan (UN DESA, 2022[8]); it is increasing in all OECD countries.

Non-adoption rates in this age group in 2020-22 across nine OECD countries for which data are available vary from 9% in Norway to 90% in Mexico, averaging 64%. They are on average five times higher than those for people between the ages of 55 and 74. A projection using data from Italy, where nearly four in five aged 75 and older in 2021 said they had never used the Internet, suggests that about one-quarter of them might remain off line by 2030.[7] In other words, non-adoption rates could remain elevated among the oldest well into the next decade.

Online activities differ in the extent to which they require education and ICT skills

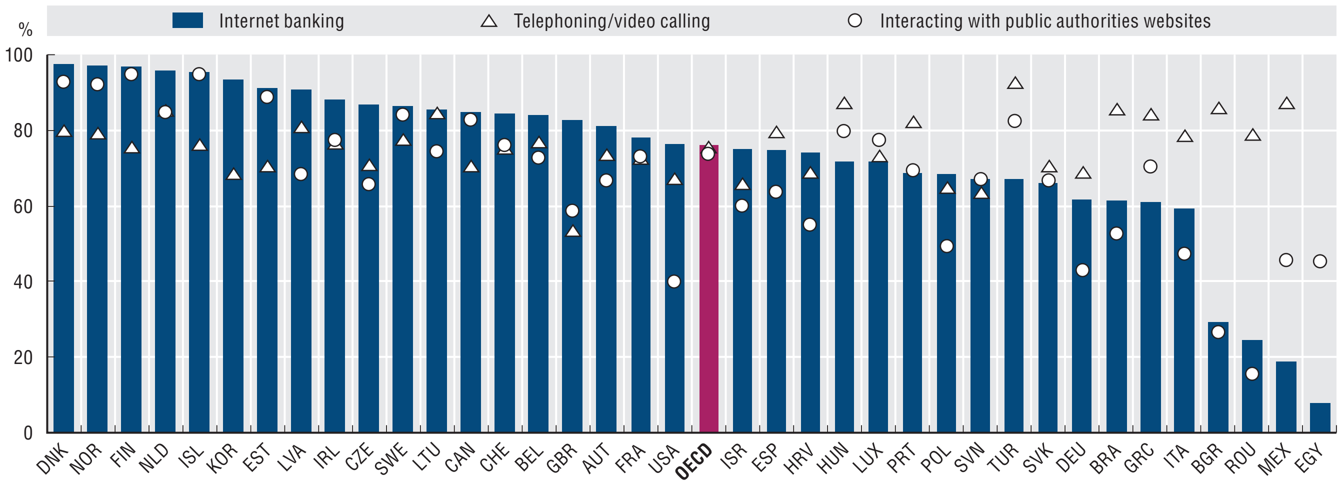
While Internet use has become the norm for a large majority of people in OECD countries, it is important to understand how they use it. Today, connectivity offers a broad range of opportunities from basic communication and information gathering to leisure activities, the purchase of goods and services, education and job hunting, and interactions with the government.

Across countries, uptake of specific online services can vary significantly. For instance, average uptake rates among Internet users of video calls and Internet banking are both around 76% (Figure 3.4). However, while uptake rates of Internet banking range from 8% to 97%, uptake rates of video calling are above 50% in all countries included here, ranging from 53% to 93%. When compared to Internet banking, an activity that would seem to require similar skills, uptake of online government services is of the same magnitude, averaging 74%. In 28 of the 37 countries for which data are available, Internet users are more likely to use Internet banking than online government services. There is also substantial variation across countries in the use of online government services, with uptake rates ranging from 15% to 95%.

Uptake rates among Internet users before the onset of the COVID-19 pandemic were regressed on three variables to better understand the forces behind the different uptake of online services across countries. These variables are the share of adults that completed tertiary education; the share of adults that have computer experience and did not fail a basic test on information and communication technologies (ICTs); and per-capita income. Results are summarised below and reported in Figure 3.5 and Annex Table 3.A.1.

Figure 3.4. Uptake of Internet banking and online government services varies across countries

Uptake of Internet banking, video calls, and interactions with public authorities' websites among adult Internet users, 2023 (or most recent)



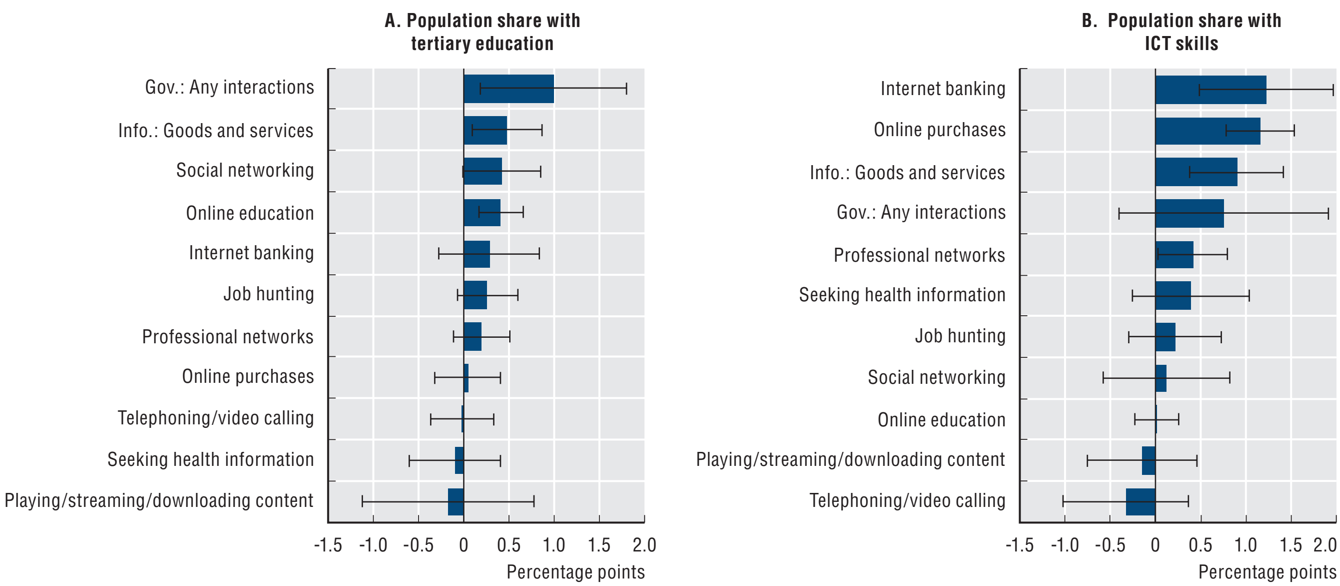
Note: See endnote 8.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/5kwtya

Figure 3.5. Online activities such as Internet banking and online purchases are correlated with formal education and ICT skills

Coefficient estimates from regressions of uptake rates of online services among Internet users, 2015-19; on formal education, 2015; share of the population with basic ICT skills, 2011-18; and GDP per capita, 2015



Note: See Annex Table 3.A.1.

Source: Authors' elaboration based on data from OECD (2023[12]; 2023[11]; 2023[5]; 2016[9]).

StatLink https://stat.link/r4o0tl

First, results show that uptake of activities such as video calling or streaming or downloading content among Internet users is uncorrelated with either formal education or ICT skills. However, formal education matters for the propensity to interact with websites of public authorities. A 1 percentage-point increase in the share of the adult population that has completed tertiary education, for example, is associated with a 1 percentage-point increase in the share of Internet users that interact with the government via the Internet. Formal education is also associated with a higher incidence of Internet use to find information about goods and services and social networking, although the effects are smaller.

Finally, there is a highly statistically significant relationship between formal education and uptake of online education services. While the effect on education is smaller here than for other activities, the estimate is large relative to the lower rate of uptake of online education – only 12 percentage points on average.

Second, even after controlling for formal education and gross domestic product (GDP) per capita, ICT skills tend to be highly correlated with activities that set up or involve monetary transactions: Internet banking, online purchases and the search for information about goods and services. The effect sizes are large: a 1.0 percentage-point increase in the share of the adult population with ICT skills is associated with a 1.2 percentage-point increase in both uptake of Internet banking and online purchases. There is also a positive, albeit smaller, partial correlation between ICT skills and participation in professional networks.

Finally, there is little to suggest that GDP per capita determines online behaviour once the effects of education and skills have been considered. Half of the coefficient estimates are negative, and most are statistically insignificant. Weak statistical significance is only observed for uptake of video calls and online purchases: a 10% increase in GDP per capita is associated with decreased uptake of video calls by 1.7 percentage points and increased uptake of online purchases by 1.3 percentage points.

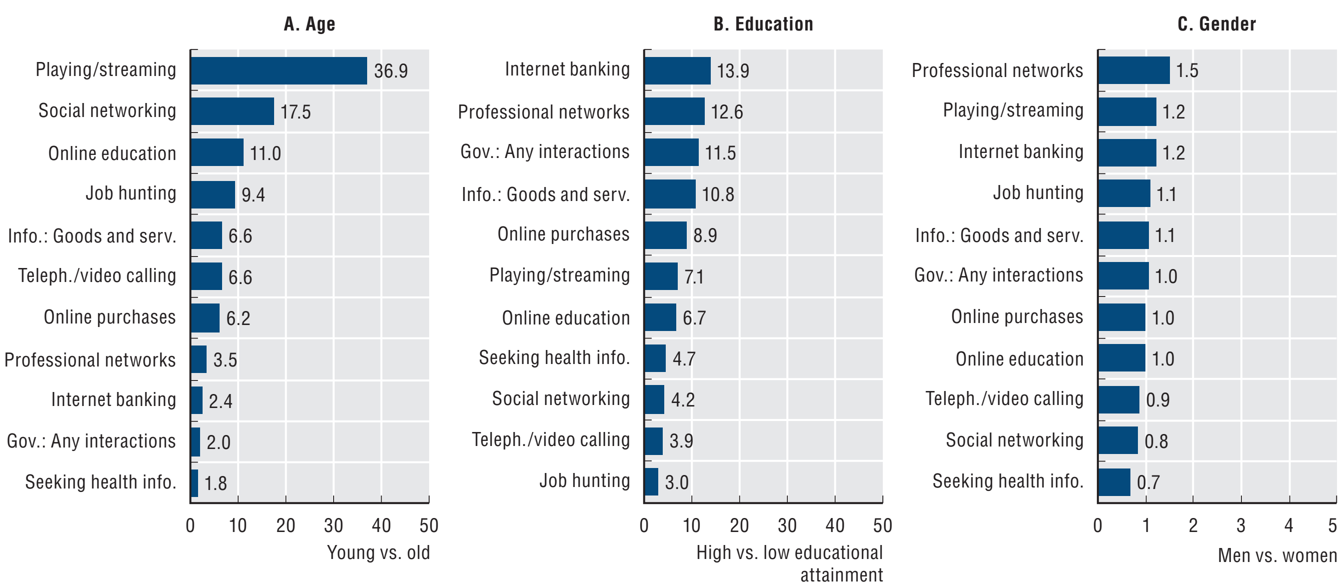
Younger and more educated Internet users engage in a larger variety of online activities

Differences across groups in uptake rates depend on the level of uptake. For instance, differences will necessarily be small if the overall uptake level in a population is either close to 100% or close to 0% (Oster, 2009[14]; Klasen and Lange, 2012[13]). Uptake rates will also depend on recall periods – the time period respondents are asked to consider in survey questions. These are typically 3 months, but this chapter uses 12 months for some indicators. It can thus be misleading to compare either absolute differences in uptake rates (i.e. in percentage points) or relative differences across different activities.

Comparing odds ratios provides a better way of understanding specific socio-economic and socio-demographic characteristics. For example, the odds of uptake among the young and elderly can be compared, where the odds are the adoption rate divided by the non-adoption rate. An odds ratio greater than unity would indicate higher uptake among the young, while a ratio below one would indicate higher uptake among the elderly. Figure 3.6 compares average odds ratios in uptake across different online activities between the young and the old; between high and low levels of educational attainment; and between men and women.

Figure 3.6. Younger and more educated Internet users engage in a larger variety of online activities

Average odds ratios for uptake rates of online services, adult Internet users, 2023 (or most recent)



Note: See endnote 8.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/ir3b8z

Overall, younger and more educated Internet users have consistently higher odds of engaging in online activities, suggesting they are more likely to embrace a larger variety of online activities. However, the importance of age and education for uptake varies significantly across different online activities. For instance, differences in the odds for Internet users from different generations are particularly large for online leisure activities and participation in social networks. They are less pronounced for activities such as online interactions with government authorities, Internet banking and participation in professional networks. The differences are the least pronounced for Internet use to access health information, for which demand will likely increase with age.

As expected, given the cross-country results above, education is associated with a higher likelihood of uptake of certain activities. These include participation in professional networks, Internet banking, interactions with government, search for information about goods and services, and online purchases. Educated Internet users also have seven times larger odds on average of using the Internet to access online education services.

Interestingly, educated Internet users have only three times larger odds on average to use the Internet for job hunting. This finding seems to result from counteracting forces. On the one hand, individuals with lower levels of educational attainment tend to face higher unemployment risks. Consequently, they are associated with a higher demand for any type of job search services (Mincer, 1991[16]; OECD, 2023[15]). On the other hand, those with higher levels of educational attainment are more likely to use online job search services. Online job advertisements also tend to be skewed towards occupations that require high levels of education (LMIC, 2020[17]).

Finally, differences in the odds of uptake of online services are far less pronounced between men and women. Female Internet users tend to be more likely to seek health information on line and to engage in social networking and video calling. Male Internet users tend to be more likely to engage in gaming and streaming, Internet banking and professional networking. Among others, this is consistent with results from a study in Norway that finds that adolescent boys are five times more likely than girls to play online video games, while girls were more likely to use social media (Leonhardt and Overå, 2021[18]).

COVID-19 led people to rely more on online services… at least temporarily

From the first few months of 2020 onward, the COVID-19 pandemic shaped trends in the usage of online services. Demand for broadband communication services soared, with some operators experiencing as much as 60% more Internet traffic than before the onset of the pandemic (OECD, 2020[19]). Telework and remote schooling became the norm for many workers and students during lockdowns. Higher demand for video conferencing services, in turn, contributed to the sharp increase in Internet traffic (Ker, Montagnier and Spiezia, 2021[20]; Aksoy et al., 2022[21]).[9] E-commerce sales also increased sharply as consumers avoided indoor venues. In the European Union, retail sales via mail order houses or the Internet in April 2020 increased by 30% year-on-year (OECD, 2020[22]). In the United States, they surged by more than 40% in 2020 (Brewster, 2022[23]). Governments were at the forefront of responding to the pandemic, including by setting up dedicated online information portals and apps to support contact tracing, store vaccination certificates, or to support working and learning from home.

Are these changes also reflected in uptake rates? The first two panels of Figure 3.7 show that before the pandemic, Internet use in the three months preceding the survey increased on average by 1.6 percentage points per year. Meanwhile, daily Internet use increased at a rate of 2.6 percentage points per year (see also Annex Table 3.A.2). For both indicators, as well as online banking, the onset of the pandemic did not significantly change this trend, suggesting that pandemic restrictions did not sway any additional non-adopters to go on line.

There is clear evidence, however, of the pandemic's impact on use of online services. Uptake rates of video calling had already increased by an average of 3.7 percentage points before the onset of the pandemic. However, the pandemic led to an additional increase by about 8.6 percentage points (panel C). In other words, the pandemic propelled uptake rates of video calls by about 2.5 years. Similarly, uptake rates of online purchases (panel E) also increased with the onset of the pandemic in 2020 by an additional 4.4 percentage points.

The pandemic also resulted in an increased share of the adult population interacting with government authorities through their websites. Uptake of any of the three interactions with the websites of government authorities covered by the data (i.e. obtaining information, downloading forms and sending information) increased by 1.8 percentage points on average prior to the pandemic (not shown). With onset of the pandemic, uptake increased by an additional 2.1 percentage points. The effects seem primarily due to an increased share of adults obtaining information through government websites in 2021 rather than more adults sending information via government online portals (see last two panels of Figure 3.7). However, after peaking in 2022 at 56%, it appears that the share of individuals obtaining information through government websites is now returning to its pre-pandemic trend. In contrast, the share of adults sending information to government authorities now exceeds the post-COVID trend.

Figure 3.7. Uptake of online services increased during the pandemic

Average uptake rates of online services and pre-pandemic trends across countries, 2016-23

Notes: Averages reported for the "Actual" series are adjusted for variation in sample sizes across years. See also notes to Annex Table 3.A.2.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/1vxzoh

More surprisingly perhaps, the pandemic had a very small and weakly significant effect on the propensity of adults to search for health information (panel D). After peaking at 59% in 2021 amid the pandemic, this rate appears to have returned to its post-pandemic trend in 2023. However, uptake rates do not capture the intensity of use. A more nuanced understanding of the effect of the pandemic on specific online activities requires different data. The likely persistence in increased use of online services is also unclear: did the pandemic increase uptake permanently or will use patterns return to the pre-pandemic trend (suggested by some of the series in Figure 3.7)? In what follows, two activities supported by digital technologies and connectivity – telework and e-commerce – are analysed more closely.

While more telework seems to be here to stay…

More telework has been positive for many people during the COVID-19 pandemic and may have brought significant welfare and productivity gains. While employers likely need to balance potential cost savings against what may be adverse effects on productivity, workers clearly value the option of working from home for two or three days every week. In a survey by Barrero, Bloom and Davis (2021[24]) among workers in the United States, half said they would be willing to forgo a 5% increase in their salary to work at home part time.

The experience with large-scale teleworking led many to wonder whether remote work is becoming a permanent feature of the future of work (OECD, 2020[25]). A pair of empirical studies by the OECD suggest the answer is "yes". The first, Adrjan et al. (2021[26]), looks at the share of online job postings in 2020 and 2021 that advertise telework, a forward-looking indicator of the adoption of telework. The authors find the share of postings advertising remote work more than tripled during the pandemic, from 2.5% in January 2020 to 8.5% in December 2021. However, while the tightening of pandemic restrictions was associated with an increased share of postings advertising remote work, the subsequent easing of restrictions did not have an analogue negative effect. In other words, while the pandemic was a catalyst for a shift towards remote work, the effect appears to be long-lasting.

In the second study, Criscuolo et al. (2021[27]) report results from an OECD survey on teleworking of both workers and managers in 25 countries. While they find differences between the two groups, with workers hoping for more telework than managers, most respondents in both groups seemed to agree on two to three working days as the ideal intensity of remote work. Empirical work based on a monthly survey in the United States suggests that preferences between managers and workers converged over the course of the pandemic. It suggests that workers have continued to supply about 30% of workdays from home from early 2022 onward (Barrero, 2022[30]; Barrero, Bloom and Davis, 2021[24]).

However, the most recent data from the monthly survey suggest the gap between employees' desired teleworking days and employers' plans has remained constant at about half a day. Moreover, recent evidence suggests a negative effect on productivity of telework (Atkin, Schoar and Shinde, 2023[28]; Emanuel and Harrington, 2023[29]). It will thus be interesting to see whether the incidence of teleworking will fall further from its pandemic peak, especially once labour markets are cooling. Finally, the benefits of telework will be distributed unequally as better paid and more educated workers are generally more likely able to work from home (Brussevich, Dabla-Norris and Khalid, 2020[31]; Garrote Sanchez et al., 2021[32]). This raises issues about equal opportunity.

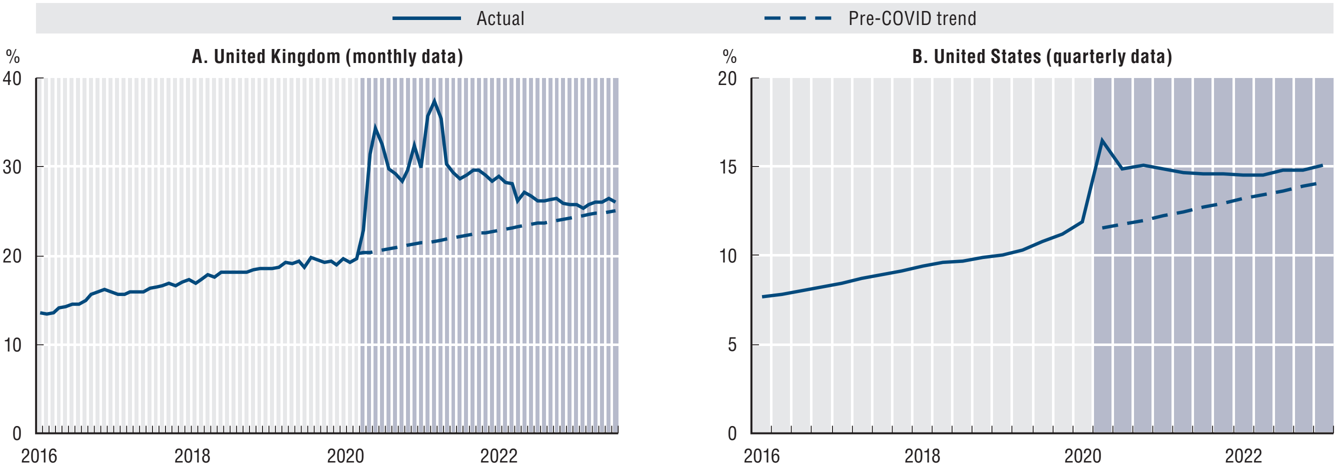
...the large uptick in e-commerce seems to be fading

While more teleworking than in the pre-pandemic era seems here to stay, the sharp increase in e-commerce observed during the pandemic seems to have been transitory. A study based on data from a major credit card provider first shows that, overall, the online share of total spending rose from 10.3% in 2019 to 14.9% at the peak of the pandemic (Cavallo, Mishra and Spilimbergo, 2022[4]). However, the most recent data (for September 2021) suggest these spikes in online spending shares were already dissipating at the aggregate level. While online spending shares remained above the pre-pandemic trend in about half of the 47 countries examined, the difference was only 0.6 percentage points on average.

This is in line with more recent data from the United Kingdom and the United States on (the narrower category of) e-commerce retail sales (Figure 3.8). At its peak in February 2021, the share of e-commerce in total retail sales in the United Kingdom had increased by 16 percentage points above the previous trend but reverted as pandemic restrictions were eased. By mid-2023, the share of e-commerce was only 0.9 percentage points above the previous trend. In the United States, for which quarterly data are available, the percentage of e-commerce in total retail sales peaked at 5 percentage points above the pre-pandemic trend. It then stabilised at about 1 percentage point above the trend during the first half of 2022. While the share of e-commerce in total retail sales continues to increase, it does so broadly in line with trends observed prior to the pandemic.

Figure 3.8. Much of the initial increase in e-commerce during COVID-19 has dissipated

E-commerce retail sales as a percentage of total sales, Q1 2016 – Q2 2023, United Kingdom and United States



Notes: Both series are seasonally adjusted. Pre-pandemic trends are estimated based on a regression of the share of online sales on the time variable for the period Q1 2016 to Q4 2019 (United States) and January 2016 to February 2020 (United Kingdom).

Source: Authors' elaboration based on ONS (2023[33]) and US Census Bureau (2023[34]).

StatLink *https://stat.link/vzf8jp*

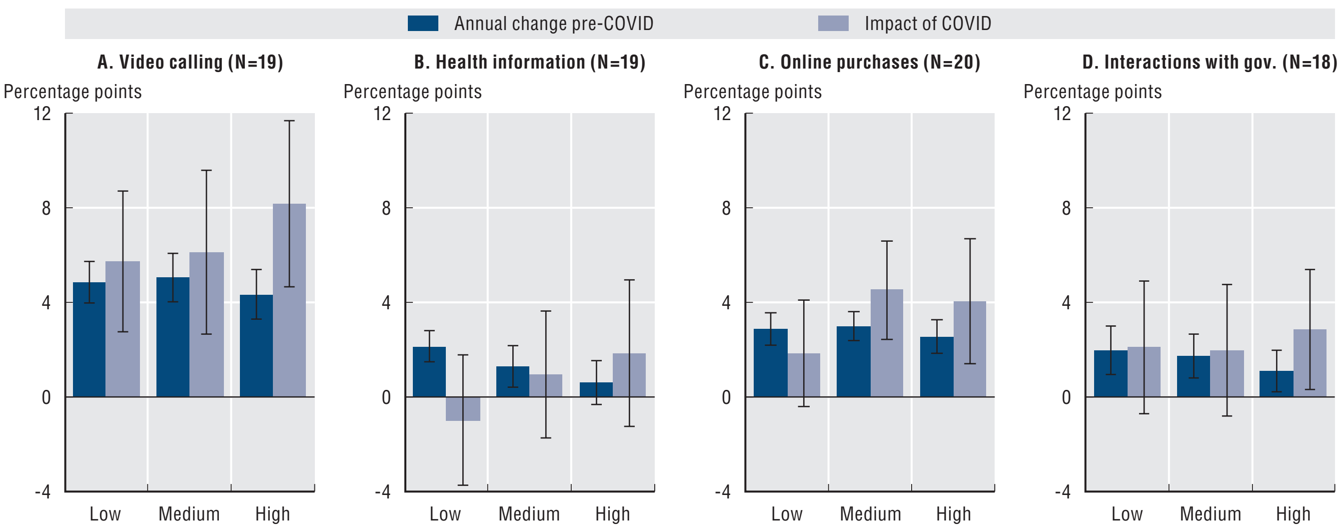
During the pandemic, those with the requisite skills were in a better position to use online services to their advantage

When COVID-19 forced people into lockdowns, the status of many online services turned from amenity to necessity. While significant digital divides were evident prior to the pandemic, evidence regarding the impact of the pandemic on these divides is only now emerging. One way to approach this question is to ask whether the onset of the pandemic affected patterns of convergence. Convergence in uptake rates between different groups can be expected at higher levels of overall uptake: those with higher levels of uptake run out of room to push the uptake rate up any further (Oster, 2009[14]).

Figure 3.9 and Annex Table 3.A.3 report estimates of the average annual change in the uptake rate prior to the onset of the pandemic and the one-off change brought about by the pandemic by level of educational attainment. Before the COVID-19 pandemic, uptake rates of those with low and high levels of educational attainment often converged, i.e. the former have tended to see large increases in uptake. This is the case for video calling; use of the Internet to access health information; and interactions with government authorities through their websites. Increases in uptake of online purchases were more evenly distributed.

Figure 3.9. COVID-19 was often associated with slowing convergence in uptake of online services

Annual changes in uptake rates and impact of COVID-19 by educational attainment, adults aged 16-74, 2016-23



Note: See Annex Table 3.A.3.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/7gnxyz

The onset of COVID-19 changed this pattern. All groups saw an additional increase in uptake of video calls, online purchases and interactions with government through their websites. However, individuals with higher levels of education typically saw the largest increase. However, in the case of Internet use to seek health information, there is no evidence for a significant increase for any group (see also Figure 3.7). This is consistent with recent research based on web search data from the United States. This research shows that individuals living in postal-code areas with lower average incomes intensified their online searches for health information to a smaller extent than those living in areas with higher incomes (Suh et al., 2022[35]).

Other indications the pandemic has further deepened digital divides. Data from a survey in Germany, for instance, suggest that women, the young, the well-educated and, most importantly, those with confidence in their digital skills, were far more likely to state that the Internet became more important for them during the pandemic (Bürger and Grau, 2021[36]).[10] Only 17.5% of those that said they had "very bad" or "rather bad" knowledge of digital technologies – nearly three in ten Germans – said the Internet had become more important for them during the pandemic. Similarly, those with university degrees were more likely to say they had used the Internet in new ways during the pandemic than those with lower levels of educational attainment (McClain et al., 2021[37]). Meanwhile, children in low-income households faced more obstacles to remote learning than those in high-income households (McClain et al., 2021[37]).

Data-dependent technologies are diffusing at a slow pace

The previous sections argued that effective use of digital technologies is becoming an important determinant of people's capacity to take part in society and make the most of economic opportunities. While uptake of online services has increased rapidly, important gaps remain that are often linked to differences in education and skills. The following section looks at adoption of digital technologies by firms.

Uneven diffusion of data-dependent digital technologies may undermine productivity growth

Sustained long-run growth depends on productivity growth, which in turn requires firms to adopt new technologies (Stokey, 2021[38]). Yet despite the increasing prominence of digital technologies in firms, labour productivity growth across OECD countries has slowed after 2005 and has not recovered (Goldin et al., 2021[39]). While there are many possible explanations for the productivity slowdown, empirical studies have pointed to faltering business dynamism (Calvino, Criscuolo and Verlhac, 2020[40]) and a pattern consistent with slowing technology diffusion from firms at the productivity frontier to those less technologically advanced (Andrews, Criscuolo and Gal, 2016[41]).

While digital-intensive sectors are on average more dynamic than other sectors of the economy – exhibiting higher firm entry, exit and job reallocation rates – they have not been exempted from the slowdown. In fact, business dynamism in digital-intensive sectors has been declining at a faster rate than in other sectors (Calvino, Criscuolo and Verlhac, 2020[40]; Calvino and Criscuolo, 2019[42]). Low-productivity firms, which tend to be younger and smaller than those at the productivity frontier, are finding it harder to catch up to the frontier in digital-intensive industries (Berlingieri et al., 2020[43]; Corrado et al., 2021[44]). Empirical work has linked the increase in productivity dispersion and market concentration, as well as faltering business dynamism, to the rise of intangible capital (which includes software and data) (Crouzet and Eberly, 2019[45]; Corrado et al., 2021[44]); the combination of proprietary software systems, data and organisational capital (Bessen, 2022[46]); or the increasing role of data in the economy (Arrieta-Ibarra et al., 2018[48]; Akcigit and Ates, 2021[47]).

Complementing these studies, this section looks at adoption rates for different digital technologies, the speed with which they are diffusing across firms and patterns of adoption by industry and firm size. It focuses on three clusters of technologies: cloud computing, a technology that relies critically on connectivity and that can be thought of as enabling flexible access to a range of other ICTs; the IoT, a suite of innovations that relies on a combination of hardware (devices equipped with sensors and microchips), software and connectivity; and big data analytics and AI, technologies that depend critically on data as an input.[11]

Uptake of data-dependent technologies such as big data analytics and AI remains low

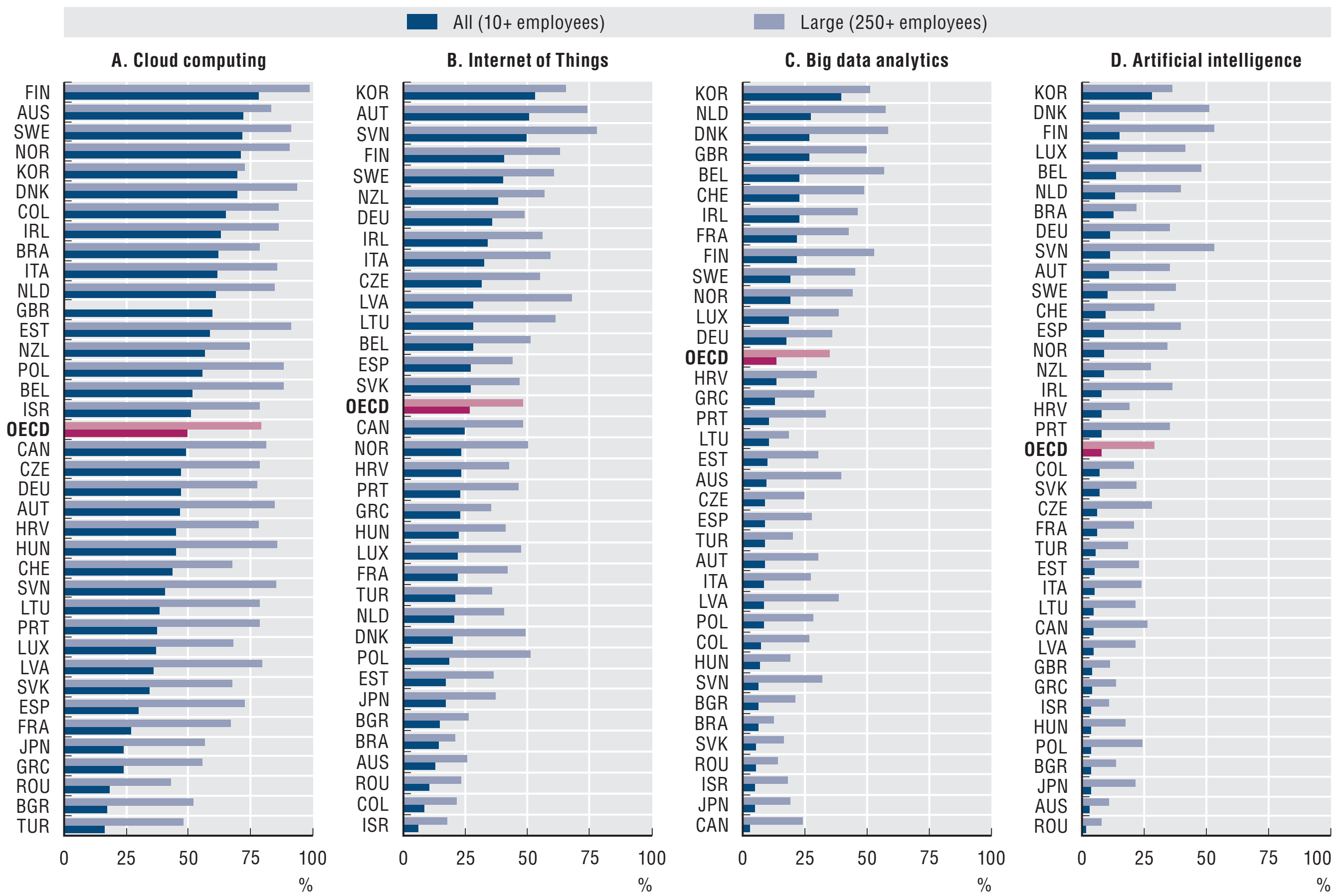
Cloud computing, IoT technologies and data-intensive technologies all had precursors, ranging back decades in some cases.[12] However, they only became available in their modern form and at scale after 2005. Nevertheless, their adoption by firms varies considerably: in the OECD, cloud computing is already used by an average of 49% of firms with ten employees and more, with adoption rates ranging from 16-78% (Figure 3.10). Adoption of IoT technologies among firms averages 27%, ranging from 6 to 53%.

By contrast, adoption rates of big data analytics and AI remain low. As of 2022, approximately 14% of enterprises with ten or more employees have embraced big data analytics on average, ranging from 3%[13] to 40%. Only 8% of firms on average used AI in 2023, with a range from 2 to 28%.[14] While the data displayed in Figure 3.10 do not include the United States, data from the Census Bureau's 2018 *Annual Business Survey* indicate that only 2.9% of firms had adopted machine learning – the data-driven subfield of AI – and only 0.7% were testing its application (Zolas et al., 2020[49]).

The use of cloud computing has been increasing since 2015 in nearly all countries for which data are available, often dramatically. Australia, Estonia, Germany, the Netherlands and Sweden all saw adoption rates increase by 30 percentage points or more. In countries with low levels of adoption in 2015 (e.g. Bulgaria and Romania), adoption rates often increased by more than 5 percentage points over just six years.

Figure 3.10. Adoption of data-driven technologies remains low

Adoption rates of cloud computing, IoT technologies, big data analytics and AI by enterprises with ten employees or more in the business sector (excluding financial services), 2023 (or most recent)



Note: See endnote 15.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/1foqhj

While data for a sufficiently large number of countries are only available for 2021 and 2022, there are several indications that IoT deployment has also increased rapidly in recent years. The number of machine-to-machine (M2M) subscriptions on mobile networks per 100 inhabitants[16] has been increasing across OECD countries between 2010 and 2021 at a rate of 19.3% per year on average (Annex Table 3.A.4). M2M is measured as the number of subscriber identity module (SIM) cards used in machines and devices (e.g. cars, smart meters or consumer electronics) that are not part of a consumer subscription.

However, from 2020 onward, IoT deployment has faced headwinds in the form of the global shortage of semiconductors, a key input in the production of IoT devices. The data on M2M SIM cards suggest the onset of the global semiconductor shortage in 2020 was associated with a one-off slowdown in the growth of M2M subscriptions per inhabitant to about 10.6% in 2020. This is substantially lower than the average over 2010-19 (Annex Table 3.A.4).

These estimates are well in line with projections by IoT Analytics, a market research firm. According to IoT Analytics (2020[51]), the number of connected IoT devices increased from 3.6 billion to 11.3 billion over 2015-20, an annual growth rate of 26%. Such devices exclude computers, laptops, fixed phones, cell phones and tablets, and one-directional devices such as those based on Radio Frequency Identification technology. However, IoT Analytics also estimates the shortage of semiconductors slowed growth in the deployment of IoT devices between 2020-21 to 8%.

Cloud computing has been diffusing three times more rapidly than big data analytics

While adoption rates for big data analytics and AI remain behind those of cloud computing and IoT technologies, they are arguably also more recent technologies. How rapidly are these technologies diffusing? Are there differences between technologies that can help explain why overall productivity growth has been slow?

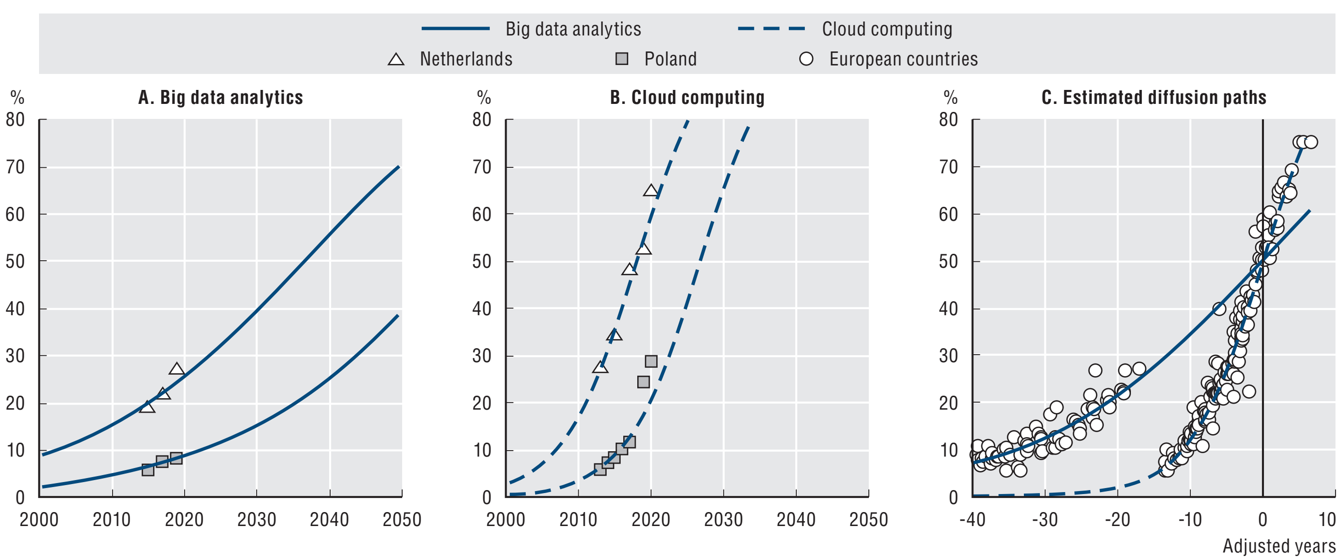
In comparing trends over time between technologies at different levels of adoption, it is important to account for different stages of diffusion. Adoption rates tend to follow an S-shaped path over time (Griliches, 1957[52]; Mansfield, 1961[54]). In other words, the relative diffusion speed, or the growth rate of the share of adopters, is high initially but converges to zero as adoption approaches 100%. Absolute changes in adoption rates, on the other hand, will initially increase and then decrease. Hence, the *level* of adoption should be considered in any comparison of how quickly new technologies diffuse. This can be done using logistic growth models that approximate the pattern described above. Figure 3.11 displays logistic functions fitted to the data on the adoption of big data analytics and cloud computing from 25 and 26 European OECD countries, respectively.[17] These functions differ across countries in terms of their location but not their shape. In other words, these technologies are assumed to diffuse at the same rate across countries for a given level of adoption.[18]

Using two countries as examples, the first two panels show that adoption of both technologies is higher in the Netherlands than in Poland. However, in line with decreasing relative diffusion speed, the relative rate of change was generally *higher* in Poland for both big data analytics and cloud computing, while the change in terms of percentage points was *lower*. Adoption of big data analytics among firms increased by 8.2 percentage points in the Netherlands over 2015-19, from 19% to 27%, corresponding to a relative change of 42.8%. In Poland, the relative increase was still higher, 43.5%, while the absolute change was substantially lower (2.6 percentage points).

Figure 3.11 (panel C) depicts the entire data for European countries and adjusts the year variable. In this way, country-specific diffusion paths are aligned and intersect at "adjusted year" zero and an uptake rate of 50%.[19] Adjusted years can be interpreted as the years passed since 50% of firms adopted a specific technology. The graph visualises the large difference in diffusion speeds between the two technologies in Europe. Based on these estimates, an increase in adoption rates from 5% to 50% takes only about 12 years on average for cloud computing. The same increase in adoption of big data analytics takes 36 years. In other words, cloud computing has been diffusing at a rate three times faster than big data analytics.[20]

Figure 3.11. Cloud computing has been diffusing three times more rapidly than big data analytics

Adoption rates of big data analytics and cloud computing by enterprises, 2000-50



Notes: Based on columns (2) and (6) of Annex Table 3.A.5. See also notes to the table.

Source: Authors' elaboration based on data from Eurostat (2022[55]).

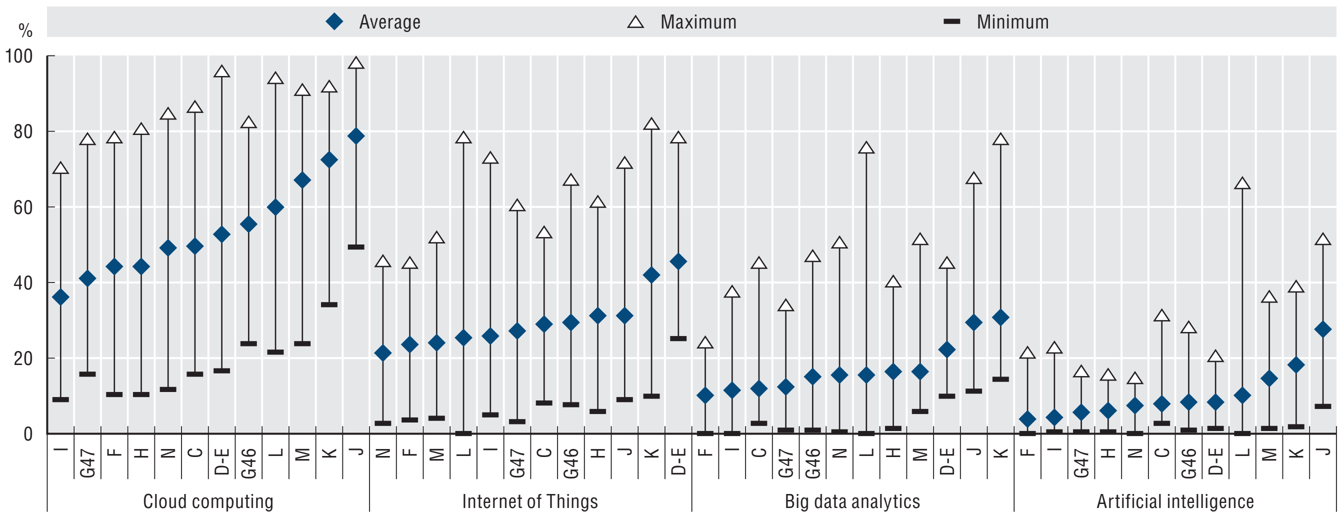
StatLink https://stat.link/s2kc7x

AI adoption is concentrated in the ICT sector

Widespread adoption of cloud computing across countries and industries underpins its rapid diffusion. Using the fourth revision of the International Standard Industrial Classification of All Economic Activities (ISIC), it is possible to identify sectors with the highest and lowest adoption rates. The highest adoption rates are typically in three main sectors: information and communication (Section J), finance and insurance (Section K) and other professional services (Section M). Meanwhile, the lowest adoption rates are found in industries such as accommodation, and food and beverage services (Section I) and retail trade (Class G47) (Figure 3.12). However, even in these industries, adoption rates are as high as 78% in some economies. This suggests that cloud computing is useful in a wide range of different settings and straightforward to adopt.

Figure 3.12. Adoption of cloud computing and IoT technologies is distributed evenly across sectors

Adoption of digital technologies by industry (ISIC codes), enterprises with ten employees or more in the business sector, 2023 (or most recent)



Note: See endnote 21.

Source: Authors' elaboration based on data from OECD (2023[5]).

StatLink https://stat.link/x4erv6

Adoption of IoT is far advanced in financial and insurance activities, as well as in the utilities sector (Sections D-E), where on average nearly half of all firms use them (OECD, 2023[50]). Apart from that, adoption of IoT technologies is remarkably evenly distributed across sectors. It ranges from an average of 21% in administrative and support service activities (Section N) to 31% in transport and storage (Section H). As expected, adoption is above average in sectors that produce and move physical objects (transport and storage, manufacturing, wholesale and retail trade) and below-average in white-collar service sectors such as real estate, and administrative and support services.

Data are abundant in the ICT sector, utilities and finance, a sector with a long history of innovation around data-driven technologies (e.g. cryptocurrencies and robo-advisers). In line with this, firms in these sectors have on average the highest adoption rates for big data analytics. Adoption of AI remains concentrated in the ICT sector, where on average nearly 28% of firms are using the technology. Beyond that, adoption rates are high in white-collar service sectors such as finance and professional services (respectively at 18% and 15%). Conversely, adoption rates are low in construction and hospitality (both at 4%). There is remarkably high variation in AI use among firms in the real estate sector, with rates ranging from 0% to 66% across countries. Overall, the finding that AI is comparatively concentrated in specific sectors is also in line with other research.[22]

Firm size is more important for adoption of data-dependent technologies and software than for IoT or cloud computing

Small firms, especially young ones, have historically played a crucial role in product innovation and productivity growth. To do so, however, they need access to recent technologies. To what extent do small, medium-sized and large firms differ in the adoption of recent digital technologies?

Across countries, larger firms tend to be more likely adopters of new technologies, including cloud computing, IoT technologies, big data analytics and AI. However, it is difficult to draw conclusions about the importance of firm size for adoption in this way as focusing on either absolute or relative differences can be misleading. In Canada, for instance, the absolute difference in adoption rates between large and small firms is 35 percentage points for cloud computing but only 23 percentage points for big data analytics. However, large firms are 15 times more likely to use big data analytics than small firms and only 1.7 times more likely to use cloud computing.

As in the case of uptake of online services, it is preferable to compare odds ratios, which under reasonable assumptions about the diffusion process will not depend on the level of uptake.[23] Large firms are three and four times more likely to adopt IoT technologies and cloud computing, respectively, than small firms on average (Figure 3.13). However, for big data analytics and AI, they are five and six times more likely, respectively.[24] Still, large firms are almost 13 times more likely to use enterprise resource planning software than small firms. Hence, firm size is a more potent predictor of adoption for data-dependent technologies in relation to IoT technologies or cloud computing but no more important than long-standing software solutions.

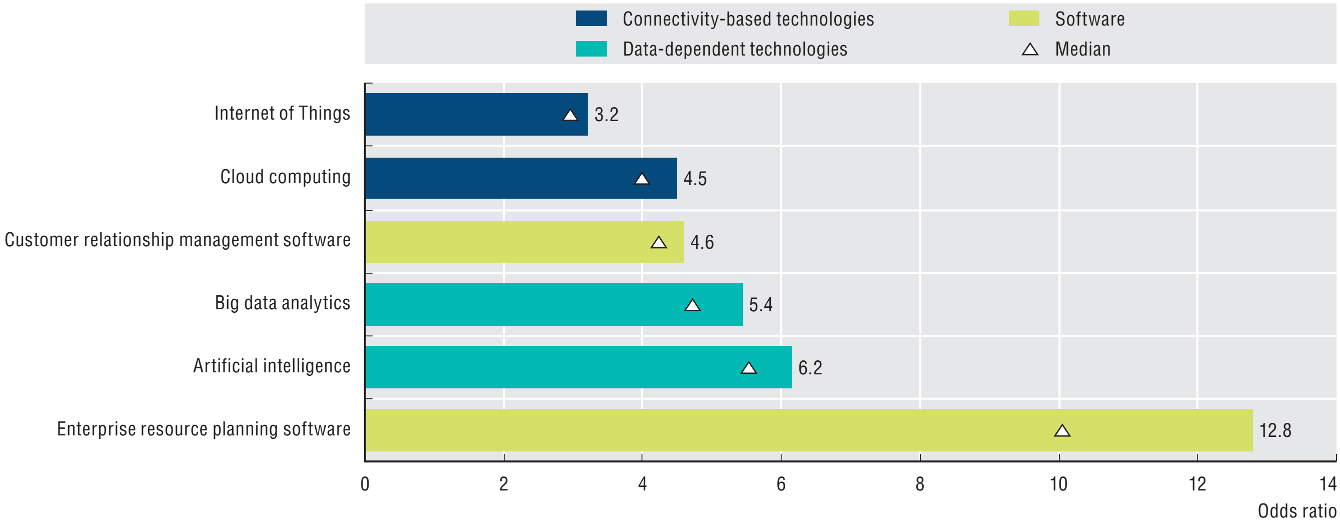
Slower diffusion of data-dependent technologies might be linked to scale economies, financial frictions or lack of access to data

The above results suggest that something about intangibles such as data and software make them less amenable to rapid diffusion. What explains these differences in diffusion speeds and uptake between small and large firms? Three possible factors are explored below.

First, the cost structure associated with the use of a technology is important. OECD (2014[56]) hypothesised that firms can leverage cloud computing solutions to reduce fixed costs by shifting capital expenditure to operating expenses. Hence, the cost of adopting cloud computing might be comparatively low for both small and medium-sized firms and start-ups. This could be critical as both are more likely to be constrained in terms of access to finance (Holton and McCann, 2021[57]).

Figure 3.13. Firm size is a more important predictor of adoption for data-dependent technologies and software than for IoT technologies or cloud computing

Average odds ratios of adoption in large enterprises vs. adoption in small enterprises, 2013-23



Note: Odds ratios are defined as the odds of large enterprises (250 employees and more) adopting a specific technology divided by the odds of small enterprises (10-49 employees).

Sources: Authors' elaboration based on OECD (2023[5]) and Eurostat (2024[95]).

StatLink https://stat.link/ivxyd1

Data-dependent technologies and software, on the other hand, have large economies of scale – the combination of high fixed costs and low costs per additional unit (Shapiro and Varian, 1999[59]; Haskel and Westlake, 2018[58]). AI and data analytics require complementary investments, not least to bring together relevant data from different silos and change organisational processes (Nolan, 2021[60]). Consequently, fixed costs will be high relative to other technologies. At the same time, marginal costs tend to be low.

For instance, a retailer that collects data from its stores to predict demand faces low costs of producing a prediction for an additional outlet. Additional computer power and data storage is cheap – not least because of cloud computing – and larger datasets typically do not require more data scientists to analyse them. In fact, adding data from further locations will typically *improve* forecasts for similar stores in different locations. Hence, the relevant variables for adoption of such a zero-marginal-cost technology are fixed costs and operational scale. Firms with larger scale face lower per-unit costs (or higher benefits relative to the fixed costs) and will thus be more likely to adopt. This logic applies to both software (a technology) and data (an input into AI and data analytics).

Second, high fixed costs point to the importance of access to funding. Smaller and younger firms typically find it more difficult to secure funding than large, well-established ones (Holton and McCann, 2021[57]). As an additional challenge, intangible assets such as data and (own-produced) software are often difficult to value, not least because their value is highly uncertain and often closely tied to their use. Banks will thus find it more difficult to accept them as collateral (Demmou and Franco, 2021[63]; Demmou, Franco and Stefanescu, 2020[62]). Hence, financial frictions that usually put smaller and younger firms at a disadvantage tend to be exacerbated when it comes to funding digital technologies based on intangible assets.

Third, large-scale firms might be in a better position to access data, which are only rarely sourced through markets but generated as a by-product of economic production (Spiekermann, 2019[67]; Cosgrove and Kuo, 2020[66]; Koutroumpis, Leiponen and Thomas, 2020[65]; OECD, 2022[64]). Larger firms tend to produce more units and have more customers and suppliers, all of which are potential datapoints. Hence, the larger the scale of a firm, the more data it can access.

A lack of access to external data would explain both slow diffusion and lower uptake among small firms. Several reports note the importance of data access, especially in the context of competition in digital markets (Furman et al., 2019[68]). However, few studies look at the impact of access to data on uptake of digital technologies or other relevant outcomes. A notable exception is Bessen et al. (2022[69]), who show that sole access to data is associated with a higher propensity to obtain venture capital funding.

Far-ranging adoption of AI might require yet more experimentation and co-invention

Finally, far-ranging adoption of AI might be premised on more experimentation and co-invention. AI has often been discussed as a general-purpose technology (GPT) (Cockburn, Henderson and Stern, 2018[70]), a term that describes a new method of producing and inventing important enough to have a protracted aggregate impact (Jovanovic and Rousseau, 2005[71]). Other GPTs such as electricity or the computer have often seen large gaps between their demonstrated potential and broad-based adoption. For instance, while the commercial potential of electricity was first demonstrated around 1880, it took another four decades before the uptake of the technology made itself felt in economic statistics (David, 1989[72]). Similarly, the ENIAC – the first programmable, electronic general-purpose digital computer – was built in 1945. Yet, in 1984, nearly 40 years later, only every fifth worker in the United States used a computer at work (Kominski, 1988[73]). Meanwhile, productivity effects associated with the computer were only observed from the mid-1990s onward (Stiroh, 2002[74]).

Agrawal, Gans and Goldfarb (2022[75]) argue that harnessing the potential of a GPT requires moving from its deployment in "point solutions" to "system solutions". Point solutions are comparatively easy to implement but have limited returns. Conversely, system solutions require substantial experimentation, co-invention and systemic changes. Point solutions that use AI comprise a far wider range of tasks in the financial industry – from fraud detection to assessment of default risks. Adopting AI for these kinds of tasks was comparatively easy as datasets were already in place and prediction was at the heart of the process.

It took system solutions for productivity gains from other GPTs to materialise. In other words, entrepreneurs had to figure out what types of systems could make the most of the new technology before they could implement these systems at scale. Yet this process requires substantial experimentation and co-invention, as well as changes to roles and up-skilling of the workforce. All that is costly, both in terms of funding and of dealing with resistance to operational changes. Data-driven technologies – and AI in particular – could well be at the same stage as electricity in the late 1800s and computers perhaps in the 1970s. The potential of the technology has been amply demonstrated. However, the introduction of system solutions that could boost productivity growth might require yet more experimentation and innovation (Juhász, Squicciarini and Voigtländer, 2020[76]).

Boosting equitable uptake and diffusion of digital technologies are vital to bridging digital divides and fostering productivity growth

This chapter finds that individuals' uptake of digital technologies continues at a rapid pace. However, it also notes challenges, including risks to equal opportunity and inclusion. The picture is more mixed across firms. Some innovations such as cloud computing and IoT technologies are spreading rapidly. Others, such as big data analytics, are diffusing far more slowly, especially among small and medium-sized firms. While these findings potentially point to a wide range of policy areas, five stand out.

First, the largest digital divides – both across and within countries – are often related to education and skills. This points to the need for education policies that better prepare individuals for an increasingly digital future. Education systems should enable individuals to use today's digital technologies effectively. However, to better prepare individuals for future technological change, these systems should also focus on metacognitive skills needed for lifelong learning. These could include learning-to-learn skills and the ability to reflect effectively on one's own knowledge, skills, attitudes and values (OECD, 2018[77]).

Second, uptake of online government services lags behind uptake of other online services such as Internet banking. This suggests that using government online services can remain cumbersome and that governments continue to find it challenging to provide public services that deliver on the potential of digital technologies (Welby and Tan, 2022[78]). Governments should lead by example in providing user-centric, inclusive online services.

Third, as pressure on service providers to shift on line increases, those most at risk of being left behind must be supported. For instance, non-adoption rates remain high among the elderly, especially women and those with low levels of education. They might continue to be elevated for years to come. Governments will need to find the right balance between investing in people's skills and ensuring they have sufficient offline support to access key services for as long as needed.

Fourth, adoption of digital technologies tends to be lower among smaller firms, especially for technologies associated with intangibles such as data and software. Smart small-business policies will aim to level the playing field for young and small firms by facilitating access to key inputs, especially finance.

Finally, adoption of data-dependent technologies is predicated on access to relevant data. Policy makers have two levers here that correspond to different data sources: increasing the sharing and re-use of data collected by private entities; and enhancing access to and usability of publicly held data. With respect to the former, the concept of data portability – the ability of a user to request that a data holder transfer to the user (or a third party) data concerning that user – has received much attention recently (OECD, 2021[79], 2021[80]).

Annex 3.A. Regression tables

Annex Table 3.A.1. Effect of education, ICT skills and income on uptake of online services

OLS regressions, adult Internet users (aged 16-74), 2019 (or most recent)

Dep. Variable: share of adult Internet users engaging in online activities	Adult population share with tertiary education		Adult population share with ICT skills		Log GDP per capita		Regression statistics	
	Estimate	SE	Estimate	SE	Estimate	SE	R-sq.	Obs.
Visiting/interacting with gov. websites (last 12 months)	0.99**	(0.41)	0.76	(0.59)	-0.02	(0.15)	0.60	22
Information about goods and services	0.47**	(0.20)	0.90***	(0.26)	-0.06	(0.11)	0.51	24
Social networking	0.42*	(0.22)	0.12	(0.36)	-0.17*	(0.09)	0.15	27
Online education	0.40***	(0.13)	0.01	(0.12)	0.02	(0.03)	0.66	24
Internet banking	0.28	(0.28)	1.23***	(0.38)	0.14	(0.13)	0.69	27
Looking for a job or sending a job application	0.26	(0.17)	0.22	(0.26)	-0.07	(0.06)	0.13	25
Participation in professional networks	0.20	(0.16)	0.41**	(0.19)	0.05	(0.04)	0.60	22
Online purchases (last 12 months)	0.04	(0.18)	1.16***	(0.19)	0.13*	(0.07)	0.82	24
Telephoning/video calling	-0.03	(0.18)	-0.33	(0.35)	-0.04	(0.10)	0.18	26
Seeking health information	-0.10	(0.26)	0.39	(0.33)	-0.05	(0.11)	0.05	26
Playing/streaming/downloading content	-0.18	(0.49)	-0.15	(0.31)	0.12	(0.11)	0.05	25

Notes: An estimate of 0.99 indicates that a 1 percentage-point increase in the share of the adult population with tertiary education is associated with a 0.99 percentage-point increase in the share of adult Internet users that use government websites. Robust standard errors (SE) in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. All regressions include a constant. Explanatory variables are i) the share of the adult population that completed tertiary education (2015); ii) the share of the adult population with basic ICT skills (2011-18); and iii) GDP per capita (2015, measured at constant prices and constant purchasing power parities). The share of the population with basic ICT skills refers to the share of those with computer experience and did not fail the OECD's Survey of Adult Skills' core ICT test (OECD, 2016[9]). In the case of online education, an observation from Mexico was excluded as an outlier. As the COVID-19 pandemic affected uptake rates at least temporarily (see below), the focus here is on uptake rates prior to the onset of the pandemic.

Source: Authors' elaboration based on data from OECD (2023[12], 2023[11], 2023[5], 2016[9]).

Annex Table 3.A.2. Effect of COVID-19 on uptake of online services

Fixed-effects OLS regressions, adult Internet users (aged 16-74), 2016-23

	Internet: Last 3 months	Internet: Daily	Video calling	Health information	Online purchases	Online banking	Gov.: Any interaction	Gov.: Obtaining information	Gov.: Sending information
Year	1.63*** (0.25)	2.56*** (0.30)	3.70*** (0.35)	1.24*** (0.39)	2.37*** (0.26)	2.67*** (0.34)	1.81*** (0.40)	1.08** (0.44)	2.67*** (0.38)
COVID-19 (=1 in 2020-22)	0.58 (0.61)	0.23 (0.58)	8.58*** (1.39)	1.72* (0.96)	4.36*** (0.61)	0.58 (0.48)	2.10** (0.97)	2.10 (1.47)	0.97 (1.32)
R-squared	0.92	0.92	0.87	0.86	0.97	0.97	0.98	0.96	0.97
Countries	37	36	34	37	36	37	34	32	34
Observations	254	250	228	246	250	247	171	169	177

Notes: An estimate of 3.70 on the year variable (column: video calling) indicates that uptake increases on average by 3.7 percentage points per year. An estimate of 8.58 on the COVID-19 variable indicates that uptake increased by an additional 8.6 percentage points in 2020. An estimate of the change in 2020 is the sum of both coefficients, 12.3 percentage points. Robust standard errors clustered at the country level are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. All regressions include country-fixed effects. Countries comprise OECD countries, Brazil, Bulgaria, Croatia and Romania.

Source: Authors' elaboration based on data from OECD (2023[5]).

Annex Table 3.A.3. Effect of COVID-19 on uptake of online services by level of education attainment

Fixed-effects OLS regressions, adult Internet users (aged 16-74), 2016-23

Level of educational attainment:	Telephoning/video calling			Finding health information			Online purchases			Interactions with government		
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Year	4.85*** (0.46)	5.06*** (0.52)	4.34*** (0.53)	2.14*** (0.33)	1.27** (0.45)	0.59 (0.47)	2.90*** (0.35)	2.99*** (0.31)	2.55*** (0.36)	1.97*** (0.51)	1.72*** (0.48)	1.09** (0.44)
COVID-19 (=1 in 2020-22)	5.75*** (1.52)	6.13*** (1.76)	8.18*** (1.80)	-1.00 (1.42)	0.94 (1.38)	1.84 (1.59)	1.85 (1.15)	4.52*** (1.06)	4.06*** (1.34)	2.10 (1.44)	1.98 (1.43)	2.84** (1.30)
R-squared	0.91	0.86	0.83	0.95	0.91	0.78	0.98	0.96	0.88	0.97	0.98	0.95
Countries/observations		19/133			19/133			20/140			18/108	

Notes: An estimate of 4.85 on the year variable indicates the share of adults that use the Internet for video calling increases on average by 4.85 percentage points per year. An estimate of 5.75 on the COVID-19 variable indicates that, in 2020, uptake increased once by an additional 5.75 percentage points on average. Robust standard errors clustered at the country level are reported in in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. All regressions include a full set of country-fixed effects.

Source: Authors' elaboration based on data from OECD (2023[5]).

Annex Table 3.A.4. Effect of the semiconductor shortage on M2M SIM cards

Fixed-effects OLS regressions, 2010-21

	Log M2M subscriptions per 100 inhabitants			Log M2M subscriptions	
	All	Excluding Iceland	Excluding Iceland	All	Excluding Iceland
Year	0.193*** (0.018)	0.192*** (0.019)		0.198*** (0.018)	0.197*** (0.019)
Shortage in 2020-21 (=1 in 2020-21)	-0.087 (0.068)	-0.135*** (0.048)	-0.138*** (0.041)	-0.088 (0.069)	-0.136*** (0.048)
Country-specific linear trends	No	No	Yes	No	No
R-squared	0.890	0.907	0.984	0.967	0.969
Countries/observations	34/339	33/328	33/328	34/339	33/328

Notes: An estimate of 0.193 on the year variable indicates the number of M2M subscriptions per 100 inhabitants increased by approximately 19.3% per year on average. An estimate of -0.087 on the shortage variable indicates a reduction by approximately 8.7 percentage points in this growth rate in 2020. Robust standard errors clustered at the country level reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. See also endnote 16 for more information on the data.

Source: Authors' elaboration based on data from OECD (2022[81]).

Annex Table 3.A.5. Diffusion of big data analytics and cloud computing

Fixed-effects OLS regressions, European countries, 2015-19 and 2013-20

	Big data analytics			Cloud computing		
	(1)	(2)	(3)	(4)	(5)	(6)
	All (2015-19)	OECD (2015-19)	All (2015-17)	OECD (2015-17)	All (2013-20)	OECD (2013-20)
Year	0.061* (0.033)	0.064* (0.035)	0.074 (0.045)	0.068 (0.053)	0.194*** (0.012)	0.196*** (0.010)
R-squared	0.825	0.800	0.918	0.881	0.952	0.958
Countries/observations	29/82	24/67	29/53	24/43	34/199	25/151

Notes: The dependent variable is the logit-transformed adoption rate, i.e. log $(S_{it}/(1-S_{it}))$, where S_{it} is the adoption rate in country i in year t. An estimate of 0.061 indicates that uptake increases by approximately 6.1% if the adoption rate is close to zero. The rate of increase halves (i.e. 3.05%) if the adoption rate reaches 50% and converges to zero as adoption approaches 100%. Robust standard errors clustered at the country level in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. All regressions include a full set of country-fixed effects.

Source: Authors' elaboration based on data from Eurostat (2022[55]).

References

Adrjan, P. et al. (2021), "Will it stay or will It go? Analysing developments in telework during COVID-19 using online job postings data", *OECD Productivity Working Papers*, No. 30, OECD Publishing, Paris, *https://doi.org/10.1787/aed3816e-en*. [26]

Agrawal, A., J. Gans and A. Goldfarb (2022), *Power and Prediction: The Disruptive Economics of Artificial Intelligence*, Harvard Business Review Press, Brighton, MA. [75]

Akcigit, U. and S. Ates (2021), "Ten facts on declining business dynamism and lessons from endogenous growth theory", *American Economic Journal: Macroeconomics*, Vol. 13/1, pp. 257-298, *http://dx.doi.org/10.1257/mac.20180449*. [47]

Aksoy, C. et al. (2022), "Working from home around the world", *Working Paper*, No. 30446, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w30446*. [21]

Andrews, D., C. Criscuolo and P. Gal (2016), "The best versus the rest: The global productivity slowdown, divergence across firms and the role of public policy", *OECD Productivity Working Papers*, No. 5, OECD Publishing, Paris, *https://doi.org/10.1787/63629cc9-en*. [41]

Arrieta-Ibarra, I. et al. (2018), "Should we treat data as labor? Moving beyond 'Free'", *AEA Papers and Proceedings*, Vol. 108, *http://dx.doi.org/10.1257/pandp.20181003*. [48]

Atkin, D., A. Schoar and S. Shinde (2023), "Working from home, worker sorting and development", *Working Paper*, No. 31515, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w31515*. [28]

Barrero, J. (2022), "The Work-From-Home Outlook in 2022 and Beyond", presentation at the 2022 meeting of the American Economic Association. [30]

Barrero, J., N. Bloom and S. Davis (2021), "Why working from home will stick", *Working Paper*, No. 28731, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w28731*. [24]

Berlingieri, G. et al. (2020), "Laggard firms, technology diffusion and its structural policy determinants", *OECD Science, Technology and Industry Policy Papers*, No. 86, OECD Publishing, Paris, *https://doi.org/10.1787/281bd7a9-en*. [43]

Bessen, J. (2022), *The New Goliaths: How Corporations Use Software to Dominate Industries, Kill Innovation, and Undermine Regulation*, Yale University Press, New Haven, CT. [46]

Bessen, J. et al. (2022), "The role of data for AI startup growth", *Research Policy*, Vol. 51/5, p. 104513, *http://dx.doi.org/10.1016/j.respol.2022.104513*. [69]

Brewster, M. (2022), "Annual retail trade survey shows impact of online shopping on retail sales during COVID-19 pandemic", 27 April, United States Census Bureau, *https://www.census.gov/library/stories/2022/04/ecommerce-sales-surged-during-pandemic.html*. [23]

Brussevich, M., E. Dabla-Norris and S. Khalid (2020), "Who will bear the brunt of lockdown policies? Evidence from tele-workability measures across countries", *IMF Working Papers*, No. WP/20/88, Washington, D.C., *https://www.imf.org/en/Publications/WP/Issues/2020/06/12/Who-will-Bear-the-Brunt-of-Lockdown-Policies-Evidence-from-Tele-workability-Measures-Across-49479*. [31]

Bundesbank (2022), *Lange Zeitreihen zur Wirtschaftsentwicklung in Deutschland* [Long time series on economic development in Germany] (database), *https://www.bundesbank.de/de/statistiken/indikatorensaetze/lange-zeitreihen/lange-zeitreihen-843330* (accessed on 6 February 2023). [82]

Bürger, T. and A. Grau (2021), *Digital Souverän 2021: Aufbruch in die digitale Post-Coronawelt?* [Digital sovereignty 2021: Departure into the digital post-corona world], Bertelsmann Stiftung Gütersloh, Germany. [36]

Calvino, F. and C. Criscuolo (2019), "Business dynamics and digitalisation", *OECD Science, Technology and Industry Policy Papers*, No. 62, OECD Publishing, Paris, *http://dx.doi.org/10.1787/6e0b011a-en*. [42]

Calvino, F., C. Criscuolo and R. Verlhac (2020), "Declining business dynamism: Structural and policy determinants", *OECD Science, Technology and Industry Policy Papers*, No. 94, OECD Publishing, Paris, *https://doi.org/10.1787/77b92072-en*. [40]

Calvino, F. et al. (2022), "Identifying and characterising AI adopters", *OECD Science, Technology and Industry Working Papers*, No. 2022/06, OECD Publishing, Paris, *https://doi.org/10.1787/154981d7-en*. [83]

Cambridge University Press (2022), "Definition of 'Data'", *Cambridge Advanced Learner's Dictionary & Thesaurus*, webpage, *https://dictionary.cambridge.org/dictionary/english/data* (accessed on 4 January 2023). [84]

Cavallo, A., P. Mishra and A. Spilimbergo (2022), "E-commerce during Covid: Stylized facts from 47 economies", *IMF Working Papers*, No. 2022/019, Washington, D.C., *https://www.imf.org/en/Publications/WP/Issues/2022/01/28/E-commerce-During-Covid-Stylized-Facts-from-47-Economies-512014*. [4]

CGIbr (2021), *COVID-19 ICT Panel: Web Survey on the Use of Internet in Brazil During the New Coronavirus Pandemic*, Comité Gestor da Internet no Brasil [Brazilian Internet Steering Committee], São Paulo, *https://cetic.br/media/docs/publicacoes/2/20210426095323/painel_tic_covid19_livro_eletronico.pdf*. [93]

Cockburn, I., R. Henderson and S. Stern (2018), "The impact of artificial intelligence on innovation", *Working Paper*, No. 24449, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w24449*. [70]

Corrado, C. et al. (2021), "New evidence on intangibles, diffusion and productivity", *OECD Science, Technology and Industry Working Papers*, No. 2021/10, OECD Publishing, Paris, *https://doi.org/10.1787/de0378f3-en*. [44]

Cosgrove, A. and J. Kuo (2020), "Why data marketplaces tend to fail", May, Harbr, *https://www.harbrdata.com/resources/blogs/why-public-data-marketplaces-tend-to-fail/* (accessed on 2 February 2022). [66]

Criscuolo, C. et al. (2021), "The role of telework for productivity during and post-COVID-19: Results from an OECD survey among managers and workers", *OECD Productivity Working Papers*, No. 31, OECD Publishing, Paris, *https://doi.org/10.1787/7fe47de2-en*. [27]

Crouzet, N. and J. Eberly (2019), "Understanding weak capital investment: The role of market concentration and intangibles", *Working Paper*, No. 25869, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w25869*. [45]

David, P. (1989), "Computer and dynamo: The modern productivity paradox in a not-too distant mirror", *The Warwick Economics Research Paper Series*, No. 339, Stanford University, Department of Economics, Stanford, CA. [72]

Défenseur des Droits (2022), *Dematerialisation of Public Services: Three Years Later, Where Are We Now?*, Défenseur des Droits, France, *https://www.defenseurdesdroits.fr/sites/default/files/atoms/files/rap-demat-num-en-02.05.22.pdf*. [2]

Demmou, L. and G. Franco (2021), "Mind the financing gap: Enhancing the contribution of intangible assets to productivity", *Economics Department Working Papers*, No. 1684, OECD Publishing, Paris, *https://doi.org/10.1787/7aefd0d9-en*. [63]

Demmou, L., G. Franco and I. Stefanescu (2020), "Productivity and finance: The intangible assets channel – a firm-level analysis", *OECD Economics Department Working Papers*, No. 1596, OECD Publishing, Paris, *https://doi.org/10.1787/d13a21b0-en*. [62]

Dey, M. et al. (2021), "Teleworking and lost work during the pandemic: New evidence from the CPS", *Monthly Labor Review*, No. July, *http://dx.doi.org/10.21916/mlr.2021.15*. [3]

Emanuel, N. and E. Harrington (2023), "Working remotely? Selection, treatment, and the market for remote work", *Federal Reserve Bank of New York Staff Reports*, No. 1061, Federal Reserve Bank of New York, New York, NY. [29]

Eurostat (2024), ICT Usage in Enterprises, Comprehensive Database, *https://ec.europa.eu/eurostat/web/digital-economy-and-society/database/comprehensive-database* (accessed on 17 January 2024). [95]

Eurostat (2022), *ICT Usage in Enterprises* (database), *https://ec.europa.eu/eurostat/web/digital-economy-and-society/data/database* (accessed on 27 January 2022). [55]

Evans, D. (2011), "The Internet of Things: How the next evolution of the Internet Is changing everything", *White Paper*, Cisco Internet Business Solutions Group (IBSG), *https://www.cisco.com/c/dam/en_us/about/ac79/docs/innov/IoT_IBSG_0411FINAL.pdf*. [85]

Friemel, T. (2016), "The digital divide has grown old: Determinants of a digital divide among seniors", *New Media & Society*, Vol. 18/2, pp. 313-331, *http://dx.doi.org/10.1177/1461444814538648*. [86]

Furman, J. et al. (2019), *Unlocking Digital Competition*, Digital Competition Expert Panel, London, *https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf*. [68]

Garrote Sanchez, D. et al. (2021), "Who on Earth can work from home?", *The World Bank Research Observer*, Vol. 36/1, pp. 67-100, *http://dx.doi.org/10.1093/wbro/lkab002*. [32]

Goldin, I. et al. (2021), "Why is productivity slowing down?", *Oxford Martin Working Paper Series on Economic and Technological Change*, No. 2021-6, Oxford Martin School, Oxford. [39]

Griliches, Z. (1957), "Hybrid corn: An exploration in the economics of technological change", *Econometrica*, Vol. 25/4, pp. 501-522, *http://dx.doi.org/10.2307/1905380*. [52]

Haskel, J. and S. Westlake (2018), *Capitalism Without Capital: The Rise of the Intangible Economy*, Princeton University Press, Princeton, NJ. [58]

Holton, S. and F. McCann (2021), "Sources of the small firm financing premium: Evidence from Euro area banks", *International Journal of Finance & Economics*, Vol. 26/1, pp. 271-289, *http://dx.doi.org/10.1002/ijfe.1789*. [57]

IoT Analytics (2020), *Total Number of Device Connections (incl. Non-IoT)*, IoT Analytics, *https://iot-analytics.com/wp/wp-content/uploads/2020/11/IoT-connections-total-number-of-device-connections-min.png*. [51]

Istat (2023), *Aspects of Daily Life: Public Use Data Files* (database), *https://www.istat.it/en/archivio/129959#:~:text=%E2%80%9CAspects%20of%20daily%20life* (accessed on 15 February 2023). [87]

ITU (2022), *World Telecommunication/ICT Indicators Database*, *https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx* (accessed on 3 March 2023). [6]

Jovanovic, B. and P. Rousseau (2005), "General Purpose Technologies", *Working Paper*, No. 11093, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w11093*. [71]

Juhász, R., M. Squicciarini and N. Voigtländer (2020), "Technology adoption and productivity growth: Evidence from industrialization in France", *Working Paper*, No. 27503, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w27503*. [76]

Ker, D., P. Montagnier and V. Spiezia (2021), "Measuring telework in the COVID-19 pandemic", *OECD Digital Economy Papers*, No. 314, OECD Publishing, Paris, *https://doi.org/10.1787/0a76109f-en*. [20]

Klasen, S. and S. Lange (2012), "Getting progress right : Measuring progress towards the MDGs against historical trends", *Ferdi Working Paper*, No. P60, Ferdi, *https://ferdi.fr/en/publications/getting-progress-right-measuring-progress-towards-the-mdgs-against-historical-trends*. [13]

Kominski, R. (1988), "Computer use in the United States: 1984", *Current Population Reports Special Studies Series*, No. 155, US Bureau of the Census, Washington, D.C., *https://www.census.gov/history/pdf/computerusage1984.pdf*. [73]

Koutroumpis, P., A. Leiponen and L. Thomas (2020), "Markets for data", *Industrial and Corporate Change*, Vol. 29/3, *http://dx.doi.org/10.1093/icc/dtaa002*. [65]

Leonhardt, M. and S. Overå (2021), "Are there differences in video gaming and use of social media among boys and girls? – A mixed methods approach", *International Journal of Environmental Research and Public Health*, Vol. 18/11, p. 6085, *http://dx.doi.org/10.3390/ijerph18116085*. [18]

LMIC (2020), "How representative are online job postings?", *LMI Insight Report*, No. 36, Labour Market Information Council, *https://lmic-cimt.ca/publications-all/lmi-insight-report-no-36*. [17]

Lohr, S. (2012), "How big data became so big", 12 August, *The New York Times*, *https://www.nytimes.com/2012/08/12/business/how-big-data-became-so-big-unboxed.html*. [88]

Mansfield, E. (1961), "Technical change and the rate of imitation", *Econometrica*, Vol. 29/4, pp. 741-766, *http://dx.doi.org/10.2307/1911817*. [54]

McClain, C. et al. (2021), "The Internet and the pandemic", 1 September, Pew Research Center, *https://www.pewresearch.org/internet/2021/09/01/the-internet-and-the-pandemic*. [37]

Mincer, J. (1991), "Education and unemployment", *Working Paper*, No. 3838, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w3838*. [16]

Montagnier, P. and I. Ek (2021), "AI measurement in ICT usage surveys: A review", *OECD Digital Economy Papers*, No. 308, OECD Publishing, Paris, *https://doi.org/10.1787/72cce754-en*. [94]

Nolan, A. (2021), "Artificial Intelligence, its diffusion and uses in manufacturing", *Going Digital Toolkit Note*, No. 12, OECD Publishing, Paris, *https://doi.org/10.1787/249e2003-en*. [60]

OECD (2023), *Aggregate National Accounts, SNA 2008 (or SNA 1993): Gross domestic product* (database), *https://doi.org/10.1787/data-00001-en* (accessed on 3 March 2023). [12]

OECD (2023), "Education at a glance: Educational attainment and labour-force status", *OECD Education Statistics* (database), *https://doi.org/10.1787/889e8641-en* (accessed on 8 March 2023). [11]

OECD (2023), "Employment by education level" (indicator), *http://dx.doi.org/10.1787/26f676c7-en* (accessed on 10 March 2023). [15]

OECD (2023), "ICT access and usage" (databases), *https://oe.cd/dx/ict-access-usage* (accessed on 17 January 2024). [5]

OECD (2023), *Measuring the Internet of Things*, OECD Publishing, Paris, *https://doi.org/10.1787/021333b7-en*. [50]

OECD (2022), "Measuring the value of data and data flows", *OECD Digital Economy Papers*, No. 345, OECD Publishing, Paris, *http://dx.doi.org/10.1787/923230a6-en*. [64]

OECD (2022), *OECD Broadband Portal* (database), *http://www.oecd.org/sti/broadband/broadband-statistics* (accessed on 20 January 2023). [81]

OECD (2021), "Data portability, interoperability and digital platform competition", *OECD Competition Committee Discussion Paper*, OECD, Paris, *https://www.oecd.org/daf/competition/data-portability-interoperability-and-digital-platform-competition-2021.pdf*. [80]

OECD (2021), “Mapping data portability initiatives, opportunities and challenges”, *OECD Digital Economy Papers*, No. 321, OECD Publishing, Paris, *https://doi.org/10.1787/a6edfab2-en*. [79]

OECD (2020), “E-commerce in the time of COVID-19”, *OECD Policy Responses to Coronavirus (COVID-19)*, 7 October, OECD Publishing, Paris, *https://read.oecd-ilibrary.org/view/?ref=137_137212-t0fjgnerdb&title=E-commerce-in-the-time-of-COVID-19*. [22]

OECD (2020), “Keeping the Internet up and running in times of crisis”, *Tackling Coronavirus (COVID-19)*, OECD, Paris, *https://www.oecd.org/coronavirus/policy-responses/keeping-the-internet-up-and-running-in-times-of-crisis-4017c4c9*. [19]

OECD (2020), “Productivity gains from teleworking in the post COVID-19 era: How can public policies make it happen?”, *OECD Policy Responses to Coronavirus (COVID-19)*, OECD Publishing, Paris, *http://dx.doi.org/10.1787/a5d52e99-en*. [25]

OECD (2020), “The potential of online learning for adults: Early lessons from the COVID-19 crisis”, *OECD Policy Responses to Coronavirus (COVID-19)*, 24 July, OECD, Paris, *https://www.oecd.org/coronavirus/policy-responses/the-potential-of-online-learning-for-adults-early-lessons-from-the-covid-19-crisis-ee040002*. [1]

OECD (2018), *The Future of Education and Skills: Education 2030*, OECD Publishing, Paris, *https://www.oecd.org/education/2030/E2030%20Position%20Paper%20(05.04.2018).pdf*. [77]

OECD (2016), *Skills Matter: Further Results from the Survey of Adult Skills*, OECD Skills Studies, OECD Publishing, Paris, *https://doi.org/10.1787/9789264258051-en*. [9]

OECD (2014), “Cloud Computing: The Concept, Impacts and the Role of Government Policy”, *OECD Digital Economy Papers*, No. 240, OECD Publishing, Paris, *http://dx.doi.org/10.1787/5jxzf4lcc7f5-en*. [56]

ONS (2023), *Internet Sales as a Percentage of Total Retail Sales* (database), *https://www.ons.gov.uk/businessindustryandtrade/retailindustry/timeseries/j4mc/drsi* (accessed on 16 February 2023). [33]

Oster, E. (2009), “Does increased access increase equality? Gender and child health investments in India”, *Journal of Development Economics*, Vol. 89/1, pp. 62-76, *http://dx.doi.org/10.1016/j.jdeveco.2008.07.003*. [14]

Perrin, A. and S. Atske (2021), “7% of Americans don’t use the Internet. Who are they?”, 2 April, Pew Research Center, *https://www.pewresearch.org/fact-tank/2021/04/02/7-of-americans-dont-use-the-internet-who-are-they*. [7]

Shapiro, C. and H. Varian (1999), *Information Rules: A Strategic Guide to the Network Economy*, Harvard Business Review Press, Brighton, MA. [59]

Spiekermann, M. (2019), “Data marketplaces: Trends and monetisation of data goods”, *Intereconomics*, Vol. 54/4, pp. 208-216, *http://dx.doi.org/10.1007/s10272-019-0826-z*. [67]

Stephany, F. et al. (2020), “Distancing bonus or downscaling loss? The changing livelihood of US online workers in times of COVID-19”, *Tijdschrift voor Economische en Sociale Geografie*, Vol. 111/3, pp. 561-573, *http://dx.doi.org/10.1111/tesg.12455*. [89]

Stiroh, K. (2002), “Information technology and the U.S productivity revival: What do the industry data say?”, *American Economic Review*, Vol. 92/5, pp. 1559-1576, *http://dx.doi.org/10.1257/000282802762024638*. [74]

Stokey, N. (2021), “Technology diffusion”, *Review of Economic Dynamics*, Vol. 42, pp. 15-36, *http://dx.doi.org/10.1016/j.red.2020.09.008*. [38]

Suh, J. et al. (2022), “Disparate impacts on online information access during the Covid-19 pandemic”, *Nature Communications*, Vol. 13/1, p. 7094, *http://dx.doi.org/10.1038/s41467-022-34592-z*. [35]

UN DESA (2022), *World Population Prospects 2022* (database), *https://population.un.org/wpp* (accessed on 20 December 2022). [8]

Universal Postal Union (2022), *Postal Statistics 2021* (database), *https://www.upu.int/en/Publications/Statistics/Postal-Statistics-2021* (accessed on 13 February 2023). [91]

US Census Bureau (2023), “E-Commerce Retail Sales as a Percent of Total Sales”, *ECOMPCTSA* (database), retrieved from FRED, Federal Reserve Bank of St. Louis, *https://fred.stlouisfed.org/series/ECOMPCTSA* (accessed on 13 February 2023). [34]

US Census Bureau (2022), *County Business Patterns* (database), *https://www.census.gov/programs-surveys/cbp/data/datasets.html* (accessed on 17 February 2023). [90]

Varian, H. (2019), “Artificial intelligence, economics, and industrial organization”, in Agrawal, A., J. Gans and A. Goldfarb (eds.), *The Economics of Artificial Intelligence: An Agenda*, University of Chicago Press, Chicago, IL. [92]

Welby, B. and E. Tan (2022), “Designing and delivering public services in the digital age”, *OECD Digital Toolkit Notes*, No. 22, OECD Publishing, Paris, *https://doi.org/10.1787/e056ef99-en*. [78]

Zolas, N. et al. (2020), “Advanced technologies adoption and use by U.S. firms: Evidence from the annual business survey”, *Working Paper*, No. 28290, National Bureau of Economic Research, Cambridge, MA, *http://dx.doi.org/10.3386/w28290*. [49]

Notes

1. Authors' elaboration based on data from Universal Postal Union (2022[91]), Bundesbank (2022[82]) and US Census Bureau (2022[90]) and population figures come from the UN DESA (2022[8]). Data from the Universal Postal Union (2022[91]) show a decrease in the number of permanent postal offices per inhabitant in most OECD countries since at least 2017.
2. Estimates based partly on imputations and using population data from UN DESA (2022[8]) accessed on 24 January 2024.
3. The most recent observation refers to 2023 except for Canada, Colombia, Egypt, Japan, Korea and Mexico (2022), Iceland, Israel and the United States (2021) and the United Kingdom (2020). The earliest observation refers to 2005 except for Bulgaria, France and Romania (2006), Croatia and the United States (2007), and Brazil and Colombia (2008). No data are available for 2005-08 for Canada, Costa Rica, Egypt and Switzerland. The reference period is three months prior to the survey except for the United States (six months in 2021 and no reference period in 2007), and Colombia and Japan (12 months). Data refer to age groups 16-74 years except for Costa Rica (18-74) and Israel (20-74). The OECD observation is based on a simple average of all available OECD countries.
4. Gaps are defined as the difference in uptake rates between men and women, the elderly (aged 55-74) and the young (16-24), individuals with high levels of educational attainment and individuals with low levels of educational attainment, and individuals residing in households in the fifth quintile of the household income distribution and individuals in households in the first quintile.
5. The reference period in the underlying surveys is the last three months preceding the survey. For the United States, the reference period is six months. Observations are for 2023 except for Canada, Egypt, Korea and Mexico (2022), Iceland, Israel and the United States (2021), and the United Kingdom (2020). Data refer to age groups 16-74, 16-24 and 55-74 except for Costa Rica (18-74 and 18-24) and Israel (20-74 and 20-24). The OECD observation is based on a simple average of all available OECD countries.
6. The finding that digital divides decrease in birth year has also been documented elsewhere (Friemel, 2016[86]).
7. This projection is based on a simple logistic model fitted to the pooled data from Istat's *Aspects of Daily Life* surveys for 2015-21 (2023[87]) that includes a linear time trend and fixed effects for different age groups.
8. Uptake among Internet users is estimated by dividing the uptake rate for a given activity by the share of individuals that have used the Internet over the relevant time period (typically 3 months, 12 months in the case of interactions with public authorities' websites and online purchases). Data refer to 2023 except for Canada, Egypt, Korea and Mexico (2022), Iceland and the United States (2021), and the United Kingdom (2020). For Israel, data refer to 2021 except for interacting with public authorities' websites (2020). For telephoning/video calling and Internet banking, the reference period is 3 months prior to the survey, except for Korea (12 months) and the United States (6 months). For online interactions with public authorities, the reference period is 12 months except for Brazil (3 months). For Israel, the data provided correspond to individuals aged 20 to 74 instead of 16-74. For Mexico, data on telephoning/video calling include only "Internet telephone conversations (VoIP)". Data on online interactions with public authorities include the following categories: "communicate with the government", "consult government information", "download government formats", "fill out or send government forms", "perform government procedures" and "comment on government consultations". For the United States, Internet banking also includes investing, paying bills on line and other financial services.
9. The pandemic also affected online labour markets, markets for tasks that can be done remotely on either an hourly or a per-task basis, as well as jobs in the local online gig economy (e.g. delivery or ridesharing app drivers). See, for instance, Stephany et al. (2020[89]) and CGI.br (2021[93]).
10. The finding is based on a set of two logit regressions, which are not reported here, with 814 observations using data collected by Bürger and Grau (2021[36]). In the first, the share of respondents stating that "the Internet is more important today for me than prior to the pandemic" is regressed on gender and age, as well as binary variables capturing income bracket and level of educational attainment. The second regression also controls for self-reported digital skills. The skills question is phrased as follows: "Asked in general terms, how good do you consider your knowledge of digital technologies and the Internet – their areas of application, their risks, but also

their opportunities and benefits for you and society?" and possible answers were "very bad", "rather bad", "rather good" and "very good". Age and gender were found to be statistically significant in both regressions, with women and the young more likely to state that the Internet became more important for them. As expected, those with high levels of self-reported digital skills were significantly more likely to state that the Internet became more important for them during the pandemic. Finally, while the income variables were statistically insignificant in both regressions, the effect of education appeared to be mediated by digital skills, i.e. the education variables were only statistically significant in the first regression.

11. The term "data" refers to either "information, especially facts or number, collected to be examined and considered and used to help decision-making", *or* "information in an electronic form that can be stored and used by a computer" (emphasis added) (Cambridge University Press, 2022[84]). The use of the term in this chapter corresponds to the first definition.
12. An early precursor of cloud computing was time-sharing, the sharing of computing resources among many users, which was popularised in the 1960s and 1970s. However, modern cloud computing became available with the creation of Amazon Web Services (in 2002) and the introduction of *Simple Storage Services* and *Elastic Compute Cloud* (in 2006). IoT technologies also had many precursors (e.g. radio-frequency identification technology) and the first appliance was connected to the ARPANET in the early 1980s. However, today's IoT was "born" sometime between 2008 and 2009 when, for the first time, there were more devices connected to the Internet than individuals (Evans, 2011[85]). Similarly, the systematic and strategic use of data in economic production predates the big data era by decades. However, the high-volume, high-frequency datasets used in big data analytics became available only with increasing Internet use and uptake of online services, with some commentators pointing towards 2012 as the year in which big data entered the mainstream (Lohr, 2012[88]). Finally, the term "artificial intelligence" was coined in the 1950s. However, practical applications such as machine learning arrived more recently (Varian, 2019[92]).
13. The low rate of uptake in Canada of big data analytics may be due to specificities of the survey instrument.
14. It is not clear whether survey respondents are always in a good position to answer questions about the use of AI. In particular, AI applications are often embedded as components of larger systems, which makes it more difficult to recognise them, and cognitive testing tends to indicate that respondents with limited AI knowledge can find it difficult to know whether AI technologies are used (Montagnier and Ek, 2021[94]).
15. While adoption is defined typically as current use, for Japan, adoption refers to use in the three-year period 2019-21. For Australia, observations relate to the fiscal year 2021/22, ending on 30 June 2022. For countries in the European Statistical System, sector coverage consists of all business economy activities except financial services (NACE Rev. 2 Sections B-N except for K). For Canada, the North American Industry Classification System is used instead of ISIC Rev.4. For Switzerland, observations refer to enterprises with five persons employed or more. For cloud computing, data relate to 2023 except for Switzerland (2019), Colombia and Israel (2020), Brazil, Canada, and the United Kingdom (2021), and Australia, Korea and New Zealand (2022). For IoT, data relate 2021 except for Australia, Korea and New Zealand (2022), and Colombia and Israel (2020). For big data analytics, data relate to 2022 for Australia and Korea, to 2021 for Brazil, Canada and Japan, to 2020 for Colombia, Israel and Switzerland, and to 2019 for all other countries. For AI, data relate to 2023 except for Colombia, Israel and the United Kingdom (2020), Brazil, Canada, Japan and Switzerland (2021), and Australia, Korea and New Zealand (2022).
16. M2M SIM cards data are provided to the OECD by communications regulators that collect them directly from network operators according to common definitions. Dongles for mobile data and tablet subscriptions are excluded. The significant growth of M2M in Iceland is due to the provision by Vodafone Iceland of M2M subscriptions for the benefit of international pharmaceutical companies to manage the transport of COVID-19 vaccines.
17. Data refer to enterprises with ten or more employees. Eurostat only started to survey the use of AI and IoT in enterprises in 2020.
18. This assumes that uptake rates eventually reach 100%.
19. The assumption of a common diffusion speed across countries appears justifiable in the case of cloud computing and somewhat less so for big data analytics. The simple logistic model (i.e. controlling only for differences in levels across countries) accounts for 95.8% of the variation in the data in the case of cloud computing and 80.2% in the case of big data analytics (Annex Table 3.A.5). However, of the 20 countries for which data are available for both 2015 and 2019, 6 experienced a decrease in adoption of big data analytics, something that cannot be consistent with an upward-sloping diffusion path.
20. The Eurostat survey questionnaire changed with respect to how respondents were asked about their use of big data analytics between survey year 2018 (which asked about use in 2017) and 2020 (which asked about use in 2019). Using only the 2016 and 2018 data did not affect the estimate (see Annex Table 3.A.5). The adoption rates

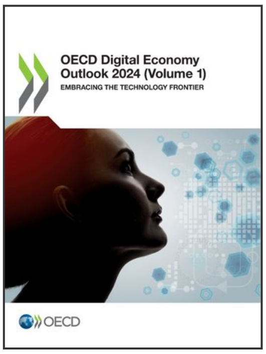
and ratios depicted in Figure 3.11 were computed for the period from 2015 to 2019. Subsequent data are not taken into account, as the perimeter of the definition for “Big data analytics” in the Eurostat survey has been modified (data for the 2023 Eurostat survey do not refer to “big data analysis” but to “data analytics”).

21. ISIC sector codes are as follows: C: manufacturing; D-E: electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities; F: Construction: G46: Wholesale trade (except repair of motor vehicles and motorcycles); G47: retail trade (except repair of motor vehicles and motorcycles); H: transportation and storage; I: accommodation and food service activities; J: information and communication; K: financial and insurance activities; L: real estate activities; M: professional, scientific and technical activities; N: administrative and support service activities. For European countries using the Eurostat Community Survey on ICT Usage and E-commerce in enterprises, data for big data analytics refer to 2019. See also endnote 20.

22. Nolan (2021[60]), for instance, observes that AI adoption in manufacturing remains low – even in most advanced economies – while Calvino et al. (2022[83]) find that a large share of AI adopters are active in the information and communication sectors and professional services.

23. Odds ratios are independent of the level of uptake if the diffusion process follows a logistic map.

24. Differences in odds ratios between different technologies are highly statistically significant jointly (p-value<0.001).



From:

OECD Digital Economy Outlook 2024 (Volume 1)

Embracing the Technology Frontier

Access the complete publication at:

https://doi.org/10.1787/a1689dc5-en

Please cite this chapter as:

OECD (2024), "Digital technology diffusion and data", in *OECD Digital Economy Outlook 2024 (Volume 1): Embracing the Technology Frontier*, OECD Publishing, Paris.

DOI: https://doi.org/10.1787/3053763a-en