OECD Skills Outlook 2019

THRIVING IN A DIGITAL WORLD

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THRIVING IN A DIGITAL WORLD

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BETTER POLICIES FOR BETTER LIVES

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Foreword

Technological progress is transforming societies, economies and people's lives as never before. The way we work, learn, communicate and consume is being turned upside-down by digitalisation. As artificial intelligence and machine learning begin to reveal their potential, the new wave of change seems set to roll on for decades.

Citizens, firms and countries that can harness digitalisation stand to benefit hugely, as it enriches lives, boosts productivity and makes learning easier. But those that do not have the capacity to tap into its power risk being left far behind. Digitalisation's promise conceals a threat – that it could widen existing inequalities and create new ones, as some jobs disappear and some skills become outmoded.

This edition of the *OECD Skills Outlook* shows that by enabling people to acquire the necessary broad mix of skills, countries can ensure today's technological revolution improves lives for all. Drawing on the Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC), this report identifies the gaps that digitalisation threatens to widen and the best ways to bridge those gaps – in the workplace, the classroom, at home, within countries and between countries.

In the workplace, digital technology is contributing to a new wave of automation. Robots are taking on more and more routine tasks, displacing workers from some jobs. At the same time, workers in other jobs can call on ever more sophisticated technology to help them perform their tasks better. In this landscape, it is urgent for countries to focus on building the skills of workers whose jobs are at high risk of automation.

To thrive in a digital workplace, workers need a broad mix of skills – strong cognitive and socio-emotional skills, as well as digital skills. The digital revolution makes the same kind of skills mix necessary in all walks of life. Without basic skills, citizens are locked out of the benefits the Internet can offer, or limited to its most elementary uses. Policies need to offer everyone ways to get the most out of the new technology. This is particularly true for regions that are already lagging behind. This report addresses squarely the risk that digitalisation could exacerbate geographical inequalities within countries.

The continuum of skills required by digitalisation underlines the need for every country to foster lifelong learning. This means breaking down inequalities in learning opportunities, adapting school curricula to changing skills requirements – including digital skills – and giving teachers the best training possible. It also means building adult education and training systems that respond to the labour market.

To achieve these goals and make the most of digitalisation, it is crucial that countries put in place a comprehensive package that co-ordinates policies on education, the labour market, tax, housing, social protection, and research and innovation. Policies on skills and training must form the cornerstone of such a package and are essential to ensure the digital transformation contributes to inclusive growth. In our rapidly digitalising world, skills make the difference between staying ahead of the wave and falling behind.

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Executive summary

New digital technologies, including information and communication technologies (ICTs), artificial intelligence and robotics, are reshaping the way people live, work and learn. Digitalisation presents immense potential to boost productivity and improve well-being. It can give people more power over what they learn, where and when they work, and how they engage in society. However, it can also increase inequalities if some people or regions are left behind. By improving the skills of their populations, countries can ensure the new technologies translate into better outcomes for all. This requires a comprehensive and co-ordinated policy intervention, with skills-related policies as the cornerstone of this package.

Skills are crucial to thrive in a digital world of work and society

Skills help bridge social divides in the access and use of digital devices

A growing number of everyday activities can be performed online. While not everyone needs to carry out complex and diverse tasks using new technologies, people should be able to build the skills they need to join the digital world.

- As broadband Internet access expands, the lack of adequate skills has become an increasingly important reason why some people do not have Internet at home. As Internet use expands, the digital divide – which initially concerned gaps in Internet access – is increasingly defined by the different ways in which people are able to use the Internet and the benefits they derive from their online activities.
- A good level of literacy, numeracy and problem-solving skills in technology-rich environments is the key that allows people to unlock all the benefits of Internet use and use the Internet in diversified and complex ways rather than just for information and communication.
- Navigating the web is becoming increasingly complex. Internet users require conceptual and cognitive skills to grasp what lies behind online information. Different sets of cognitive skills have different impacts on the types of actions people take on line. A good level of cognitive skills also increases the likelihood that people protect their privacy and security on line. More skilled parents and children may also be better prepared to counter the risks of cyberbullying or excessive Internet use.

Skills help workers adapt to changing labour markets in a digital world of work

Digitalisation is transforming the way many jobs are carried out. The pace at which new technologies are being developed is accelerating, raising anxieties about whether they will soon make some workers redundant. At the same time, the digital transformation is creating new opportunities and jobs. Reaping the full benefits of digitalisation will ultimately depend on the ability of each country to develop a set of policies that help workers adapt to these changes and develop relevant skills to thrive in the digital world.

- Technology can replace workers in routine tasks that are easy to automate and complement workers in tasks that require creativity, problem solving and cognitive skills. As machine learning and artificial intelligence advance in many sectors, a growing number of workers may need to move from declining occupations (which are highly intensive in low-skilled routine tasks) to growing ones (which are characterised by high-level, non-routine cognitive skills).
- To thrive in the digital workplace, workers will need not only digital skills but also abroad mix of skills, including strong cognitive and socio-emotional skills. High-level ICT skills will also be increasingly important in growing occupations linked to new technologies.
- Countries are facing important training challenges. Training policies will need to facilitate the transition of workers whose jobs are at high risk of being automated into new and better-quality jobs. As labour markets evolve in response to digitalisation, governments need to find the right balance between policies that foster flexibility and labour mobility, and policies that ensure job stability.
- As technology alters the importance of certain jobs in the labour market, governments will need to invest in education and training that helps workers to change job or even occupation so that they can benefit from new job opportunities and reduce the risk of losing their jobs.
- This report adopts a pragmatic approach and analyses the skills distances that separate occupations at high risk of automation from others. It looks at the cognitive skills and the skills involved in performing tasks on the job that are required for workers to change occupation and how much training is needed to facilitate these transitions. Acceptable transitions, with moderate wage reductions and limited skills excesses, can be identified for just over half of occupations with a small training effort.
- Preliminary analyses suggest that the implied training costs of helping workers move away from occupations at risk of automation can be substantial but are difficult to assess precisely. The costs of enabling labour market transitions will vary from country to country, reflecting factors such as differences in the shares of employment in jobs at high risk of automation, the costs of education and training policies, the indirect costs of training, and the occupational and skills distributions of the population.

Countries are unequally prepared to seize the benefits of digital transformation

- A small group of countries, including Belgium, Denmark, Finland, the Netherlands, New Zealand, Norway and Sweden, are ahead of other countries in their exposure to digitalisation. Their populations are also well equipped with adequate skills and supported by effective lifelong learning systems that enable them to benefit from digitalisation.
- Other countries, such as Japan and Korea, have great potential to make the most of digital transformation but need to adopt a range of policies to ensure older workers and adults are not left behind.
- In Chile, Greece, Italy, Lithuania, the Slovak Republic and Turkey, individuals and workers often lack the foundation skills necessary to flourish in a digital world. In

these countries, lifelong learning systems, both formal and non-formal, need to be strengthened substantially to enable upskilling or reskilling throughout life.

Developing a comprehensive policy package with skills-related policies as a cornerstone

Digitalisation brings many new learning opportunities

In schools, the use of technology can help students develop skills for a digital future, foster innovative ways of teaching and mitigate school failure. Access to ICT infrastructure in schools is widespread in most OECD countries: by 2015, almost 9 in 10 students had access to computers in schools. However, mere access to and use of computers is not enough to enhance student performance. Technology's effect on student outcomes depends on how it is integrated in the classroom to support teaching and learning practices. Teachers' digital competencies are instrumental to make the most out of new technologies in the classroom. Many countries should revisit the way technology is integrated into the curriculum and into pedagogical practices.

Open education and massive open online courses (MOOCs) offer new ways to acquire and diffuse knowledge, and develop skills throughout life. Highly educated and highly skilled adults are still more likely than low-skilled adults to use MOOCs, however, so their potential for skills development could be exploited further.

Policies need to support lifelong and life-wide learning for all

Strengthening lifelong learning is key for all workers and citizens to adapt to changes in the world of work and in society. International evidence shows that strong lifelong learning systems rely on a combination of targeted policies that enhance the accessibility and quality of education and training provision across all stages of life and all types of learning.

Countries can foster lifelong learning by addressing inequalities in learning opportunities throughout life, adapting the school curriculum to changing skills requirements and providing more effective training to teachers. They also need to ensure that adult education and training systems can respond to labour market changes, and to adapt systems of recognition and certification of skills to ever-evolving skills needs.

Policies also need to mitigate the geographical impact of digitalisation

The benefits of digitalisation have been highly concentrated in cities and high-tech regions, although there are signs that some firms start to take advantage of digital technologies to locate outside high-tech regions and escape high living costs. Open education and MOOCs can also help bridge geographical divides, by providing access to tertiary education for young people and workers and offering high-quality educational and training resources to teachers in schools. In this way, new technologies can mitigate inequalities due to an absence of high-quality teachers, a lack of training opportunities or a lack of access to sources of information. However, skills gaps emerge at an early age between children of different socio-economic status and different geographical location. To bridge these gaps and help lagging regions catch up, high quality skills-related policies are needed, extending from early childhood education to vocational education and training, as well as equal opportunities to continue education.

The policy effort needs to be co-ordinated

The need to foster lifelong learning and the need to prevent geographical inequality both require a comprehensive approach to digital transformation that co-ordinates a range of skills and development policies and actors. As highlighted in the OECD's Going Digital and Future of Work initiatives, close alignment is crucial between policies on education, the labour market, tax, housing, social protection, development, and research and innovation. Skills-related policies must form the cornerstone of this policy package so that digitalisation enhances well-being and productivity. The OECD stands ready to work with countries and to play its part in the collective effort to ensure everyone thrives in a digital world.

Chapter 1. Overview – Skills-related policies to work, live and learn in a digital world

Digitalisation transforms economies and societies, triggering new policy challenges. Countries' preparedness to seize the benefits of digital transformation is largely dependent on the skills of their populations and the range of appropriate policies put in place, with skills-related policies as a cornerstone. This chapter proposes a scoreboard to capture countries' performance in terms of skills, digital exposure and skills-related policy effort. It assesses the extent to which countries have been, are and will be able to make the most of digitalisation through their population's skills. The chapter provides an overview of the publication. It investigates how policies, particularly those related to skills development and use, can shape the outcomes of digital transformation and ensure that the new technological wave leads to prosperity and better lives for all.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

Digitalisation changes many aspects of peoples' lives

Economies and societies are undergoing a *digital transformation*. Information and communication technologies (ICT), artificial intelligence (AI) and robotics are profoundly changing the way people work, interact with one another, communicate and live. Digital technologies have also enabled the rise of the "platform economy", which has introduced new ways to work, create value and socialise. These changes prompt new policy challenges.

These technologies can reduce some inequalities between individuals. Now people can supply their skills in a more flexible way by using online platforms, rather than a unique formal employer, blurring the frontiers between standard and non-standard forms of employment. Some people can work from anywhere by teleworking, hence benefiting from job creation regardless of the location of the firm. Anybody can access educational content on line at zero or very low cost, even content created by academics from top universities. They can easily communicate with their friends and families who are far from them, share ideas and make them easily available to many people simply by going on line. People from anywhere can buy products from everywhere.

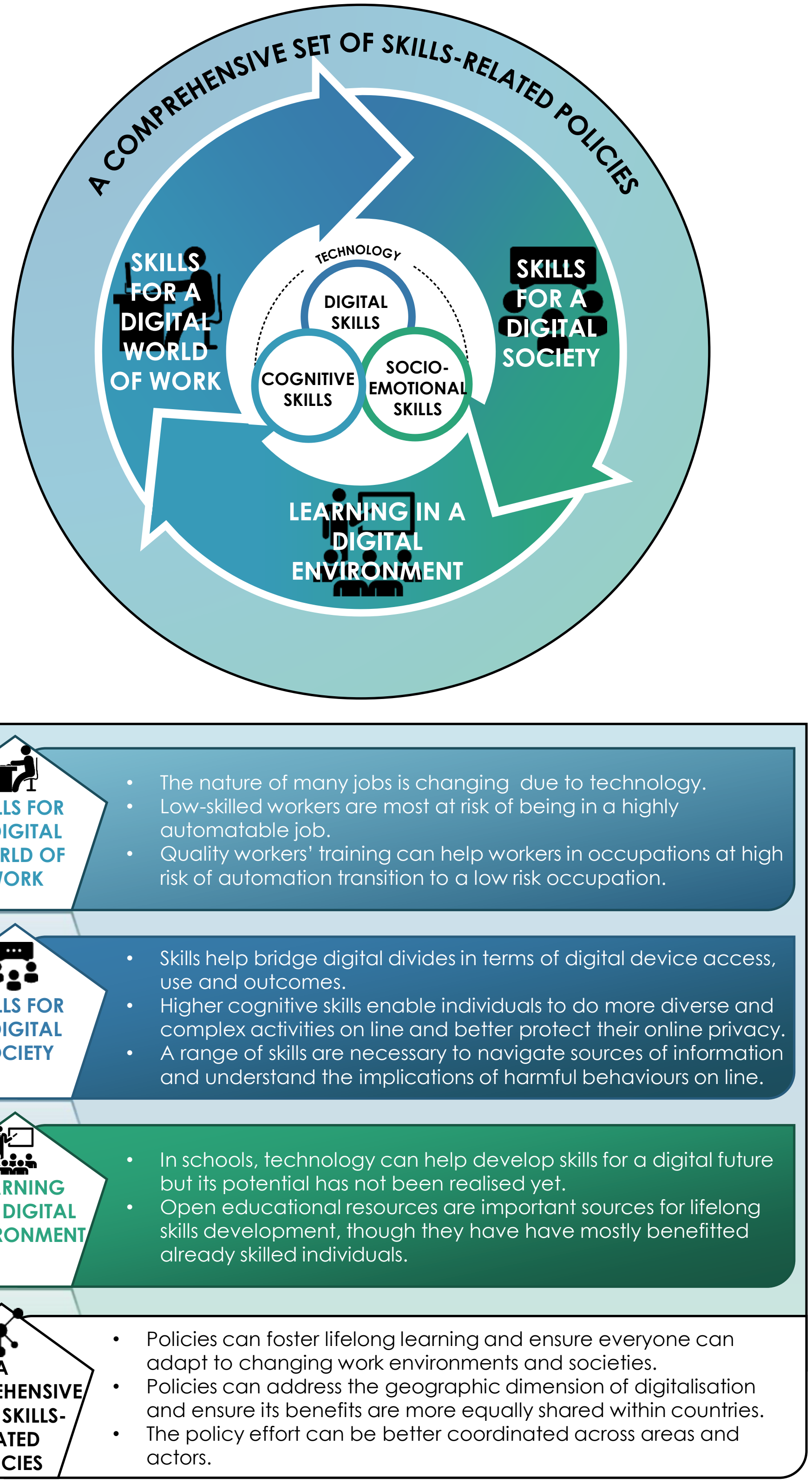
However, digital transformation can also lead to divergence:

- *Between workers*: those who are high-skilled and can easily adapt to a digitalised workplace, and those with low levels of skills who are most likely to bear the costs of digital transformation; those in rapidly growing firms that have adopted the most recent technology, who can learn from technology and develop highly demanded skills, and those in firms with old work practices. Divergence can also develop between workers in different sectors and occupations that are affected differently by technology. Those working through online platforms do not have the same rights and social protection as workers under standard contracts.
- *Between firms*, with a small share of them accounting for a large share of profits.
- *Between regions*, with some attracting high-tech firms, high-paid jobs, and a high-skilled population while others lag behind or stagnate, experiencing lay-offs and a shrinking population.
- *Between individuals*, with children spending an increasing amount of their time on line and older people feeling more isolated as many activities are now done on digital devices; with highly skilled adults performing many activities on line and low-skilled ones performing fewer or simpler tasks using the Internet.

While some argue that the current wave of technological change is broader and quicker than past ones, technological change has always been part of economies and societies. It has contributed to productivity growth, but skill-biased technological change has also increased inequalities, with highly skilled individuals benefiting the most. Many uncertainties remain about how the current technological transformation will affect workers, economies and societies. Rather than wait to see what those effects are, it is preferable to adopt a pro-active approach that builds resilience now.

The purpose of this publication is to understand how policies, particularly those that affect skills development and use, can shape the outcomes of digital transformation and ensure that the benefits are more equally shared among and within countries' populations (Figure 1.1).

Figure 1.1. Skills for a digital world



SKILLS FOR A DIGITAL WORLD OF WORK

- The nature of many jobs is changing due to technology.
- Low-skilled workers are most at risk of being in a highly automatable job.
- Quality workers' training can help workers in occupations at high risk of automation transition to a low risk occupation.

SKILLS FOR A DIGITAL SOCIETY

- Skills help bridge digital divides in terms of digital device access, use and outcomes.
- Higher cognitive skills enable individuals to do more diverse and complex activities on line and better protect their online privacy.
- A range of skills are necessary to navigate sources of information and understand the implications of harmful behaviours on line.

LEARNING IN A DIGITAL ENVIRONMENT

- In schools, technology can help develop skills for a digital future but its potential has not been realised yet.
- Open educational resources are important sources for lifelong skills development, though they have have mostly benefitted already skilled individuals.

A COMPREHENSIVE SET OF SKILLS-RELATED POLICIES

- Policies can foster lifelong learning and ensure everyone can adapt to changing work environments and societies.
- Policies can address the geographic dimension of digitalisation and ensure its benefits are more equally shared within countries.
- The policy effort can be better coordinated across areas and actors.

In several countries, inequalities have reached their highest level in 50 years. The average disposable income of the richest 10% of the population in OECD countries is now more than nine times that of the poorest 10% (OECD, 2016[1]). Perhaps more importantly, inequalities of opportunities are high in many countries. Children whose parents did not complete secondary school have significantly fewer chances of making it to university than their peers who have at least one parent who achieved tertiary-level education (OECD, 2016[2]). About a third of children of manual workers remain manual workers themselves (OECD, 2018[3]). In this context, the urgency for policies is to ensure that the new technological wave does not simply add to existing inequalities.

Investing in skills, education and training is needed to make the most of digital transformation

OECD member countries spent from 3% to 6% of their GDP on educational institutions in 2015 (OECD, 2018[4]). However, 1.5% to 19% of young tertiary-education graduates (depending on countries) have low literacy and numeracy skills as evidenced by the Survey of Adult Skills (PIAAC). Thirteen percent of 15- to 29-year-olds were not in employment, education or training (NEET) in 2017. This suggests there may be imbalances between the type of skills and knowledge developed during education and those demanded by employers, although labour market regulations and other aspects also play important roles (OECD, 2018[4]). Raising the number of years of education is not *per se* the solution. Enrolling a larger share of the population in tertiary education can be costly and may not necessarily lead to the right skills mix for all.

Moreover, some skills may be best developed on the job. While there are no comparable data for adult learning and on-the-job training, some countries have or are implementing ambitious plans for adult training. However, high-skilled workers are, on average across OECD countries, almost three times more likely to participate in training than low-skilled ones.

Investing in skills, education and training is necessary to make the most of digital transformation. Many countries face challenging questions, however, about how this investment can become more efficient and inclusive and whether current investments are enough.

Countries are unequally prepared to seize the benefits of digital transformation

The extent to which countries have been, are and will be able to make the most of digitalisation through the skills of their population and the policies they put in place is summarised here in a scoreboard (Table 1.1). The scoreboard is structured around three main dimensions: 1) skills needed to benefit from digitalisation; 2) exposure to digitalisation; 3) skills-related policies to make the most of digital transformation.

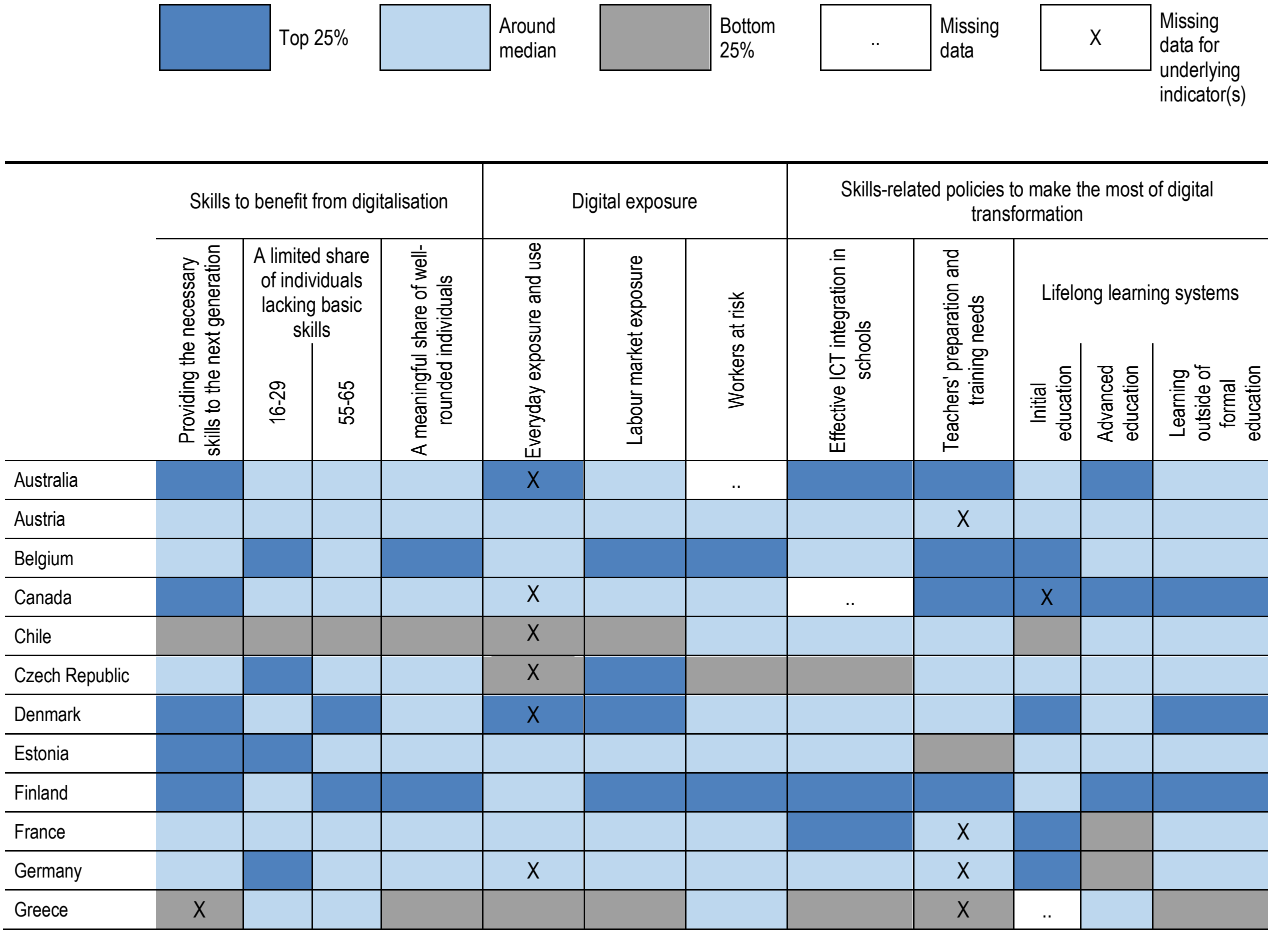
The scoreboard shows that:

- No country achieves above-median outcomes in all the dimensions of the scoreboard, suggesting that all countries have room for improvement.
- A small group of countries, including Belgium, Denmark, Finland, the Netherlands, New Zealand, Norway, and Sweden, tends to fare very well in most dimensions. Their populations are, broadly speaking, well-equipped in terms of skills and supported by robust lifelong systems to benefit fully from digitalisation. These countries are also ahead in terms of the exposure to digitalisation of their economies and societies.

- Other countries such as Japan and Korea perform unequally depending on the dimension considered. Though they perform well on indicators closely linked with the skills acquired in formal education and those of the young generation's skills, they perform around average or poorly when it comes to labour market exposure and learning outside of formal education. These countries have potential to make the most of digital transformation but would have to adopt a range of policies to ensure older workers and adults are not left behind.
- Chile, Greece, Italy, Lithuania, the Slovak Republic and Turkey tend to perform poorly in many dimensions. Their populations often lack the necessary foundational skills to flourish in a digital world, both as individuals and workers. Moreover, their lifelong learning systems, both formal and non-formal, are not developed well enough to enable workers to upskill or reskill throughout their lifetimes, a crucial issue in a quickly changing world.

The scoreboard also shows that the skills of a country's population and its skills-related policies are strongly linked to its exposure to digitalisation, which in a way captures the adoption of technologies at work and at home. Almost all countries with low exposure to digitalisation (Chile, Greece, Italy, Lithuania, the Slovak Republic and Turkey) tend to perform relatively badly in the skills levels and skills policies dimensions.

Table 1.1. Scoreboard on skills and digitalisation



🟦 Top 25%

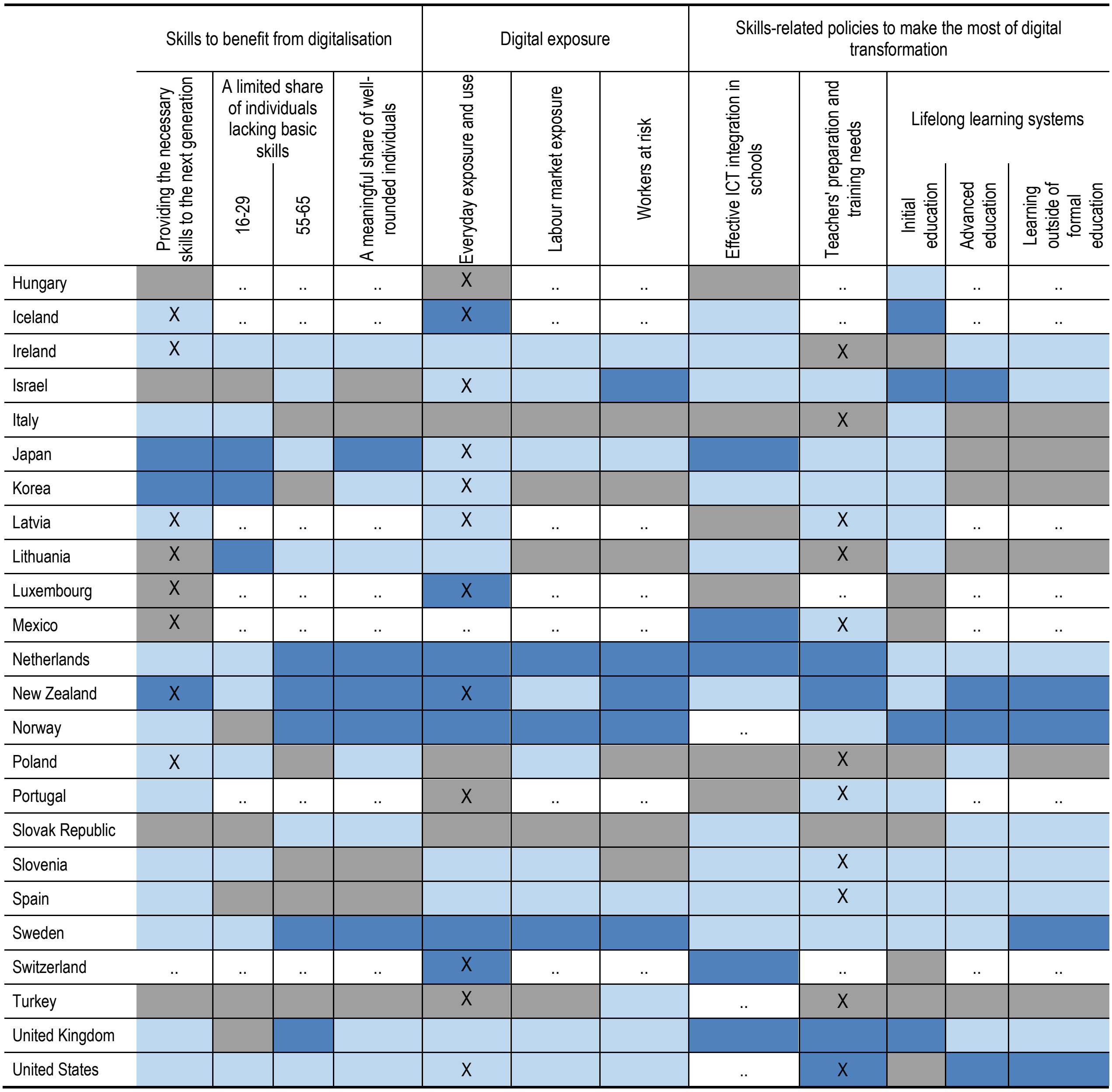
░ Around median

▓ Bottom 25%

.. Missing data

X Missing data for underlying indicator(s)

	Skills to benefit from digitalisation				Digital exposure			Skills-related policies to make the most of digital transformation				
	Providing the necessary skills to the next generation	A limited share of individuals lacking basic skills		A meaningful share of well-rounded individuals	Everyday exposure and use	Labour market exposure	Workers at risk	Effective ICT integration in schools	Teachers' preparation and training needs	Lifelong learning systems		
		16-29	55-65							Initial education	Advanced education	Learning outside of formal education
Australia	🟦	░	░	░	🟦 X	░	..	🟦	🟦	░	🟦	░
Austria	░	░	░	░	░	░	░	░	░ X	░	░	░
Belgium	░	🟦	░	🟦	░	🟦	🟦	░	🟦	🟦	░	░
Canada	🟦	░	░	░	░ X	░	░	..	🟦	🟦 X	🟦	🟦
Chile	▓	▓	▓	▓	▓ X	▓	░	░	░	▓	░	░
Czech Republic	░	🟦	░	░	▓ X	🟦	▓	▓	░	░	░	░
Denmark	🟦	░	🟦	░	🟦 X	🟦	░	░	░	🟦	░	🟦
Estonia	🟦	🟦	░	░	░	░	░	░	▓	░	░	░
Finland	🟦	░	🟦	🟦	░	🟦	🟦	🟦	🟦	░	🟦	🟦
France	░	░	░	░	░	░	░	🟦	░ X	🟦	▓	░
Germany	░	🟦	░	░	░ X	░	░	░	░ X	🟦	▓	░
Greece	▓ X	░	░	▓	▓	▓	░	▓	▓ X	..	░	▓



	Skills to benefit from digitalisation				Digital exposure			Skills-related policies to make the most of digital transformation				
	Providing the necessary skills to the next generation	A limited share of individuals lacking basic skills		A meaningful share of well-rounded individuals	Everyday exposure and use	Labour market exposure	Workers at risk	Effective ICT integration in schools	Teachers' preparation and training needs	Lifelong learning systems		
		16-29	55-65							Initial education	Advanced education	Learning outside of formal education
Hungary		..	..	..	X	..	..		..		..	..
Iceland	X	..	..	..	X	..	..		..		..	..
Ireland	X								X			
Israel					X							
Italy									X			
Japan					X							
Korea					X							
Latvia	X	..	..	..	X	..	..		X		..	..
Lithuania	X								X			
Luxembourg	X	..	..	..	X	..	..		..		..	..
Mexico	X	..	..	..	..	..	..		X		..	..
Netherlands												
New Zealand	X				X							
Norway								..				
Poland	X								X			
Portugal		..	..	..	X	..	..		X		..	..
Slovak Republic												
Slovenia									X			
Spain									X			
Sweden												
Switzerland	..	..	..	..	X	..	..		..		..	..
Turkey					X			..	X			
United Kingdom												
United States					X			..	X			

Notes: The scoreboard shows for each sub-dimension countries that perform in the top 25%, bottom 25%, and those around the OECD median. A sharp threshold has been applied and therefore, some countries can be classified in one group (e.g. the bottom 25%) but be close to the other group (e.g. median). For all performance levels (top 25%, around median and bottom 25%), cells that display "X" indicate missing data for underlying indicator(s). Countries are ranked according to the sub-dimensions, which are aggregates of the indicators presented in Annex Table 1.A.1 (see Box 1.1 for details regarding the aggregation and the sub-dimensions of the indicators). For indicators based on the Survey of Adult Skills (PIAAC), data of Flanders is used for Belgium, and of England and Northern Ireland for the United Kingdom.
Sources: See Annex Table 1.A.1 for detailed sources of the underlying indicators.

Box 1.1. Scoreboard on skills and digitalisation

The scoreboard in Table 1.1 examines how countries have performed in recent years in terms of skills, digital exposure, and skills-related policies to make the most of digital transformation.

Main dimensions

Three overarching dimensions are considered, with sub-dimensions often based on a group of indicators. Many of them are taken from the analytical work presented in this edition of the OECD Skills Outlook (see Annex 1.A for the full list of indicators and their sources).

Skills to benefit from digitalisation: This dimension attempts to capture the extent to which individuals have acquired the foundational skills they need to take advantage of the benefits of digitalisation while facing its risks. As digital transformation requires individuals have a mix of skills, the three sub-dimensions evaluate proficiency in a range of skills for different age groups (15-year-olds, young adults and seniors) and different types of skills (literacy, numeracy, problem-solving skills and social skills). The focus is on people who lack baseline proficiency in a given skill, as these people will find it significantly harder to upskill or to acquire new skills. The three sub-dimensions analyse the extent to which:

- the young generation is proficient in a set of cognitive and social-emotional skills, including reading, science, mathematics, collaborative and creative problem solving (*Providing the necessary skills to the next generation*);
- younger and older generations lack basic cognitive skills, including ICT skills (*A limited share of individuals lacking basic skills*); and
- individuals have a well-rounded set of skills, combining high levels of literacy and numeracy skills (*A meaningful share of well-rounded individuals*).

Digital exposure: This dimension aims to describe how digitalisation has permeated people's everyday lives and work environments. Digital transformation has not penetrated all countries to same extent, suggesting that countries that are currently lagging behind will have to catch up soon. As such, the three sub-dimensions analyse the extent to which:

- people use digital technologies in their everyday life (*Everyday exposure and use);*
- workers' tasks may change because they become more non-routine or ICT intensive (*Labour market exposure*); and
- workers could encounter difficulties finding a new job if they were dismissed (*Workers at risk*).

Skills-related policies to make the most of digital transformation: This dimension tries to summarise how countries' skills-related policies will enable them to prepare their population for digital transformation. Teachers play a crucial role in preparing the next generation to acquire the right skills for a digital world and workers need to be able to upskill or reskill throughout their lifetime. Lifelong learning is pivotal in reaching this goal. Therefore, the three sub-dimensions evaluate:

- the gap in students' performance depending on the level of ICT use at school (*The effective integration of ICTs in schools*);
- teachers' skills and training needs in ICT (*Teachers' preparation and training needs*); and
- whether countries have lifelong learning systems that facilitate participation in learning activities from initial to advanced education, as well as in non-formal and informal learning (*Lifelong learning systems*).

Methodology

For each of the sub-dimensions of the scoreboard, a summary indicator is calculated and presented in Table 1.1. Each summary indicator aggregates the set of indicators presented in Annex 1.A. Before the aggregation, each indicator was normalised to obtain values between 0 and 1, with higher values reflecting better performance. The summary indicators for each sub-dimension are calculated as simple averages of the indicators they contain.

Countries are ranked according to the summary indicators. The scoreboard shows countries that perform in the bottom 25%, in the top 25% and those around the OECD median (in the remaining part of the distribution). A sharp threshold has been applied and therefore, some countries can be classified in one group (e.g. the bottom 25%) but remain close to the other group (e.g. median).

Most occupations are changing and workers need to adapt

The use of the Internet by most workers, the possibility of automating an increasing range of tasks and opportunities to supply skills through online platforms are different facets of digital transformation that affect what people do on the job, how and where they work. Almost all occupations are changing because of these transformations. To face these changes, most workers need to adjust their skills mix either through training or by learning on the job.

New technologies lead to both substitution and complementarity effects (Chapter 2). Technology replaces workers in the performance of some tasks that can be automated, such as routine tasks. Workers use technology, such as ICT tools, to perform their tasks differently and perhaps more efficiently. Both of these effects have implications on the mix of skills people need.

Workers need more than digital skills to adapt to these changes. The mix of skills is required to successfully navigate the transition to the digital world of work and thrive in it. Strong general cognitive skills are needed, such as literacy, numeracy and ICT skills, from basic to advanced ICT skills depending on the job. Analytical skills are required, alongside a range of complementary skills such as problem solving, creative and critical thinking, communication skills and a strong ability to continue learning. Working in growing occupations linked to new technologies requires advanced ICT skills such as coding.

Workers in different countries and in different occupations are exposed to digital technologies to a different extent (Figure 1.2). In the coming years, countries and occupations lagging behind in technology adoption may catch up progressively, which would lead to important changes for workers in those countries or occupations. Among countries covered by the Survey of Adult Skills (PIAAC), a group of countries (Denmark, the Netherlands and Sweden) is ahead in the digital transformation of the workplace, with most of their workers intensively using ICTs on the job and predominantly performing non-routine tasks. Other countries are lagging behind (Chile, Greece and Turkey). In the same vein, workers in some low-skilled occupations, such as services and sales workers or plant machine operators, or in elementary occupations, vary considerably in their exposure to digitalisation, suggesting the nature of these occupations might change as firms progressively adopt technologies.

New or growing occupations have appeared (e.g. artificial intelligence specialists, big data analysts), along with new ways to supply skills to the market. Online platforms lead to major changes in some sectors but also facilitate self-employment for a broader range of workers. People need to have the skills to benefit from these new work opportunities. So far, however, workflows on online platforms have been asymmetric, with the United States the major hiring country and Asia (South and Southeast Asia) a major provider of services. In many OECD countries, an important question is to ensure that if employers are looking for skills through online labour platforms, they are not doing so at the expense of investing in upskilling and training for their employees.

Education and training policies need to facilitate mobility across occupations

New technologies make some occupations less needed in the economy while creating others. Workers need to be mobile, or able to change occupation, to escape the risk of losing their jobs and benefit from new job opportunities. However, the skills requirements of declining occupations are likely to differ from those of growing occupations.

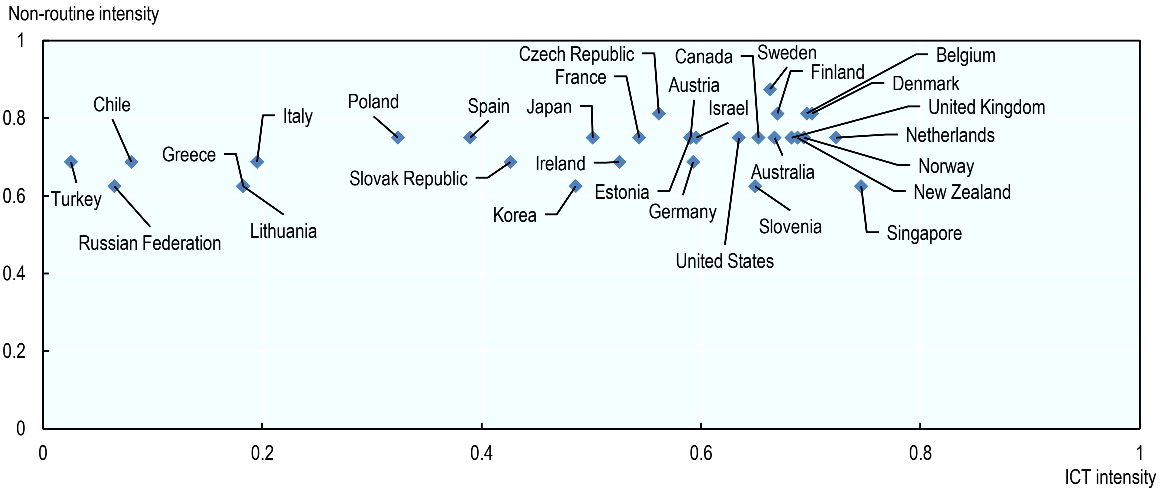
Education and training policies can aim to make it easier for workers to move from one occupation to another (Chapter 3). To limit the cost of the education and training effort, policies can facilitate transitions between occupations that are as similar as possible in terms of skills requirements.

Most occupations appear to be fairly close to some other occupations in terms of cognitive skills requirements, task content, and knowledge area, and therefore, most workers have *possible* transitions to other occupations with a relatively small training effort (approximately up to six months). However, workers may be unwilling to move to other occupations if moving entails large drops in wages and significant underuse or loss of skills. Such transitions would not be *acceptable* from individual and societal points of view. When requiring that transitions entail at worst moderate wage reductions and limited skills excesses, *acceptable* transitions can be identified for just over half of occupations with a small training effort.

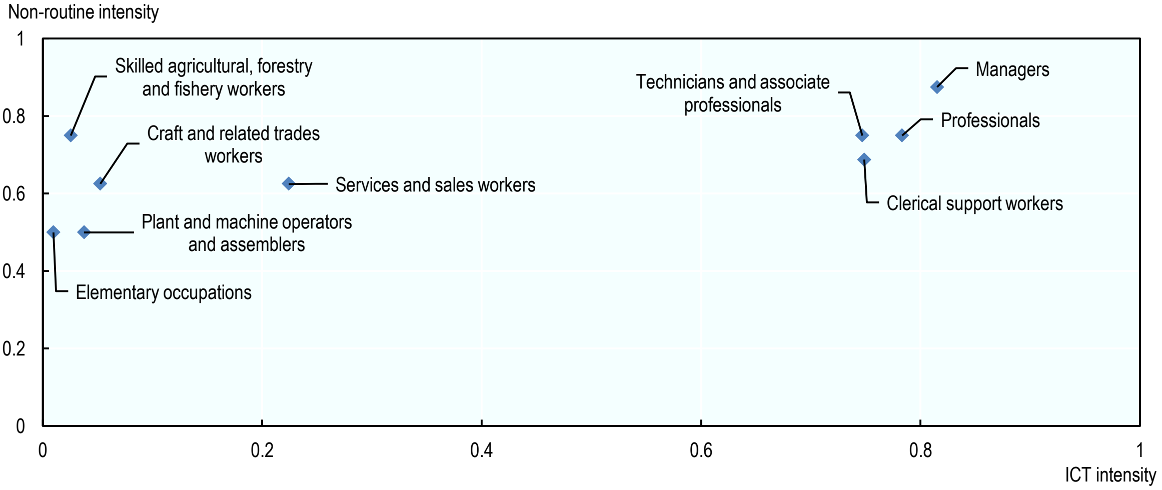
For a group of occupations, a large share of the tasks may be automatable, rendering these occupations more likely to disappear (Frey and Osborne, 2017[5]; Nedelkoska and Quintini, 2018[6]). Workers in these occupations may need to change occupation to remain in employment. To do so, they would need to adapt their skills set and perhaps acquire new skills – general and specific – and knowledge areas. While assessments of the risk of automation and of the number of jobs that may disappear remain debated, policies can target workers in those occupations to increase their mobility.

Figure 1.2. Countries' and occupations' exposure to digitalisation

Median non-routine intensity and ICT intensity of workers, by country



Median non-routine intensity and ICT intensity of workers, by occupation



Notes: The top panel plots countries' median non-routine and ICT intensities across all workers, while the bottom panel plots one-digit occupations' median non-routine and ICT intensities across all workers of that group of occupations in all countries. For example, the median non-routine intensity across all workers in Turkey is 0.7, meaning that 50% of all workers in Turkey are in jobs with a non-routine intensity above 0.7 and 50% are in jobs with a non-routine intensity below 0.7. The non-routine intensity of jobs indicator is computed following the methodology proposed by Marcolin, Miroudot and Squicciarini (2016[7]) and builds on items that capture the extent to which one's job is codifiable and sequentiable. It is close to 0 when the job is routine-intensive and to 1 when the job is not routine-intensive. The ICT intensity of jobs indicator was developed in work by Grundke et al. (2017[8]) and describes tasks associated with ICT use, from reading and writing emails to using word-processing or spreadsheet software, or a programming language. It is close to 0 when the job is not ICT-intensive and to 1 when the job is ICT-intensive. More details on the construction of the non-routine and ICT intensity indicators can be found in Chapter 2 (Box 2.3).

Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: year of reference 2015. All other countries: year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

StatLink http://dx.doi.org/10.1787/888933973076

For a proportion of occupations at high risk of automation, a relatively small training effort may be sufficient to enable *acceptable* transitions towards occupations at medium lower risk of automation. Around 10 out of 127 occupations are identified as being in a particularly critical situation, as they are at high risk of automation and an average worker in these occupations would need substantive training (of more than approximately one year) to be able to move to occupations at lower risk of automation. The share of employment in these critical occupations varies between countries and ranges from 2% to 6% if all workers in these occupations are considered to be at high risk and from 0.3% and 1.5% when only some of them are at high risk.

The required education and training effort is substantial but difficult to assess precisely

An important question for countries is to get an idea of the cost of the upskilling or (re)training required to ensure that workers at risk of losing their jobs because of automation can fin4 a new job. Trying to assess this cost is a difficult exercise that requires making several strong assumptions given available data. These assumptions can affect the size of the estimated cost. For these reasons, the analyses should be seen as aiming to foster reflection on several issues while indicating directions for policies, rather than giving precise estimates.

Chapter 3 provides estimates of the country-level minimum cost of helping workers at high risk of automation move to an occupation with a low or medium risk of automation with minimum upskilling or (re)training efforts, moderate wage reductions and limited skills excesses. These estimates range from less than 0.5% (lower bound) or 1% (upper bound) of one year’s GDP in Norway, to more than 2% (lower bound) or 10% (upper bound) of one year’s GDP in Chile. Assuming only a share of these workers are at risk gives the lower bound estimate while assuming all workers are at risk gives the upper bound estimate. Differences between countries reflect several factors, including differences in the shares of employment in jobs at high risk of automation, the costs of education and training policies, the indirect costs of training of foregone wages, and the occupational and skills distributions of the population.

These estimates mostly relate to the cost of training individuals to endow them with the cognitive skills needed in the occupation of destination. Different occupations, however, require workers to acquire several job-specific skills. Although available data present a series of caveats, an extra cost component needed to enable workers gain some job-specific skills required to move to different occupations can be added to the estimates. The training duration captured in these specific data is short, hence the extra cost component amounts to 0.06% to 0.3% of GDP, on average across the considered countries.

Estimated cost ratios may appear to be high partly because they compare costs of training that are likely to occur over several years with yearly GDP. Furthermore, workers and employers may decide to spread training over several years to reconcile (part-time) work and training. Lastly, policies should not target all workers currently employed in a high risk of automation at the same time and within one year, as technology spreads and is adopted at different paces in different countries, industries and companies.

Compared with other public expenditure, however, these estimates may appear low. This is because they only encompass the cost of education and training needed for workers who are considered the most at risk to lose their jobs and therefore may need to change occupation. However, as most occupations may change because of the development of new technologies, the education and training effort necessary to address this broader challenge is larger.

Training programmes need to be well targeted and designed

Workers in occupations at high risk of automation are particularly in need of upskilling or (re)training as they are more exposed than other workers to the risk of losing their jobs. More generally, low-skilled workers face a large skills gap that needs to be filled to adjust to changing occupations. However, workers in occupations at high risk of automation and low-skilled workers are less likely to participate in on-the-job training than other workers (Nedelkoska and Quintini, 2018[6]).

Overcoming the barriers to learning in adulthood is critical to deal with fast-changing skills demand. Countries can do this by creating flexible and shorter types of learning opportunities, improving the labour market relevance of adult learning and better recognising prior learning. It is also vital to provide a range of financial and social support to address specific barriers to learning faced by low-skilled and disadvantaged adults. In addition, countries can use targeted information and guidance to help workers move to occupations with similar skills requirements but lower risk of automation and raise awareness of the returns to skills (Chapter 3).

The specific type of training required to help workers in occupations at high risk of automation move to occupations with lower risk includes, in addition to training in general cognitive skills (literacy and numeracy), training predominantly in non-cognitive skills, such as management, communications and self-organisation. Such workers also require some training in ICT (Chapter 3). Most workers receive very short training mostly on job-specific skills that are unlikely to facilitate occupation transitions. Education and training providers, employers and labour unions can better co-ordinate their actions to provide training options that match workers' needs for career progressions and transitions.

Flexible options to combine work and learning are needed

Estimates of the effort each country needs to make to help workers move away from occupations at high risk of automation assume that people do not work when they participate in training, which leads to a large indirect cost coming from foregone wages. To reduce the cost of the training effort and ensure countries can sustain these costs, policies should encourage working and learning at the same time through flexible education and training programmes and informal learning.

Policies aiming to send workers back to formal education and training institutions can be costly unless those institutions provide flexible programmes for workers. On-the-job training programmes may be less costly and may teach job-specific skills better. On-the-job training tends to be very fragmented in most countries, however, and in many cases little is known about its quality. Programmes in formal education and training institutions might still be a preferred option when workers have to develop a range of skills including general cognitive ones. Overall, the approach needs to be tailored to workers' specific needs and build on the strengths of countries' education and training providers and programmes.

Workers are more likely to maintain their skills in workplaces more exposed to digitalisation (Chapter 2). Digital environments help workers retain problem-solving skills in technology-rich environments while non-digital environments may lead to skill obsolescence. As digital transformation affects sectors and firms differently, it may exacerbate the skills gaps and inequalities between workers in sectors and firms (mainly large firms) at the forefront of technology adoption and those in sectors and firms lagging behind. Policies can remove some of the barriers to technology adoption by firms and sectors lagging behind – for example, by improving broadband access – to ensure all workers develop the necessary skills.

The potential of open education can be exploited further

Over the last decade, open educational resources have grown significantly. A broad range of digital learning resources are offered on line freely and openly to teachers, educators, students and independent learners, (Chapter 5). Massive open online courses (MOOCs) have greatly contributed to this boost.

Open education and MOOCs offer important new sources of knowledge and skills development throughout life. The increasing take-up of MOOCs on a broad range of topics – including not only computer science but also the development of social and emotional skills – suggests that a section of the population is well aware of the need to adjust skills throughout life. As in standard adult education and training, however, adults who are already highly educated and highly skilled are more likely to participate.

In theory, open education and MOOCs offer flexible and easily accessible ways to develop skills that firms could use for on-the-job training, but this potential is not being realised at the moment, despite initiatives in this area. This is partly because their content does not match fully with employers' needs and their quality is uneven. Evidence suggests they are mostly used by those who combine work and formal education and to a lesser extent by those who are only employed.

Governments can work with education and training providers, employers, job-search agencies and MOOC platforms to broaden participation in open education, expand the use of these courses on the job, and define standards and good practices to better signal their quality and certify acquired skills. More data are needed to better understand how people may learn through MOOCs, even if they follow only a fraction of the content and do not complete the entire course.

New technologies also transform everyday life and societies

The ubiquity of smartphones and Internet connections affects many aspects of daily life in ways that are still difficult to apprehend fully (Chapter 4). These changes lead to both opportunities and challenges. Using smartphones, tablets or computers, people can do a range of activities easily from anywhere. New technologies offer great potential for spreading knowledge, improving political engagement and increasing efficiency of public services, as well as enabling new forms of leisure.

However, the development of online activities and the fact that younger and younger children are spending an increasing amount of time on line raise three major challenges:

- Internet use tends to reproduce existing inequalities. Low-performing students are less likely than top performers to use their devices to look for information on line or read the news, for example, and more skilled individuals are more likely to follow online courses.
- Children and adolescents are exposed to new risks that may affect their skills development and their educational outcomes. The quality of parent-child interactions suffers when parents use their smartphones during these exchanges, for example. The time children spend on homework can be interrupted by use of smartphones and children can be targeted by cyberbullying and other forms of cyber harassment.
- Some individuals are left behind or feel more isolated, either because they do not participate in online activities or because online activities have replaced opportunities for social interaction, reducing people's sense of belonging to a community. Older people are particularly exposed to these risks.

Skills are important sources of divides in terms of digital devices access, uses and outcomes

As broadband access has developed, lacking skills has become an increasingly important reason for not accessing the Internet. In addition, as a growing number of activities can be performed on line and some of these activities are complex, divides between individuals concern more and more the type of uses they make of the Internet and the outcomes they get from them. People need not participate in all these activities but do need to be able to benefit from them, ensuring that Internet usage does not exacerbate inequalities.

Cognitive skills have an impact on people's participation in online activities. Four profiles of Internet users emerge from the analysis in Chapter 4 (which is based on data from some European countries): i) diversified and complex use; ii) diversified but simple use; iii) use for practical reasons and iv) use for information and communication. Lacking basic literacy and numeracy skills is a barrier to performing activities on line and belonging to any of these profiles. Lacking basic problem-solving skills in technology-rich environments is a barrier to performing diversified and complex activities. For those who participate in online activities, higher cognitive skills – whether literacy, numeracy or problem-solving skills in technology-rich environments, or a mix of them – significantly augment the probability of moving from a use mostly for information and communication to a diversified and complex use, taking other determinants into account.

Having a good level of cognitive skills also increases the likelihood that people take measures to protect their privacy and security when they go on line. People with a well-rounded set of cognitive skills, including problem-solving skills in technology-rich environments, are more able to protect themselves on line and thus reduce their exposure to digital risks. More skilled parents and children may also be better prepared to combat risks such as cyberbullying or excessive use.

However, the range of skills and values necessary to navigate among many sources of information, fully understand the implications of harmful behaviours, and adapt to new technological development goes beyond cognitive skills. Social and emotional skills, and skills that combine both cognitive and social aspects, are also likely to play an important role. Further data are needed to uncover the differential effect of some social and emotional skills and values, and more advanced digital skills, on people's capacities to make informed use of technology in their everyday lives and protect themselves from risks.

Initial education can become more forward-looking

Initial education needs to prepare young people for tomorrow's world. It should help all youth develop skills for the 21st century, adapt to changes on the labour market, have a career progression or change occupations, and become informed and responsible citizens. Leaving initial education without the necessary skills has become increasingly penalising.

New technologies change skills requirements but can also enhance learning opportunities and help develop skills for the future. The use of technology in the classroom can help develop digital skills and the complementary skills people need. In addition, digital tools can favour personalised instruction, allowing students to progress at their own pace and teachers to spend more time with learners who lag behind. Technology can enable new ways of teaching that may prevent school failure (Chapter 5).

Student assessments rarely measure computer competencies, so there is little evidence on whether technology use in schools improves students' digital skills, although a few studies find it does (Bulman and Fairlie, 2016[9])

Which digital skills should schools aim to develop? As technologies evolve rapidly, people should acquire general digital skills rather than specialised ones that risk soon becoming obsolete. Computational thinking, or the ability to frame problems in ways that computers can help solve them, is increasingly put forward as an important skill for a growing number of jobs and a way to develop wider skills, such as creativity or critical thinking. In addition, students should be able to interpret the information provided by digital tools in specific contexts, adapt to increasing numbers and types of tools while protecting their data and privacy and understanding the implications of invading others' privacy.

Technology use in schools offers multiple benefits but its potential has not been realised yet

Access to ICT infrastructure in schools is extensive in most OECD countries, where socio-economically disadvantaged students have levels of access similar to those of advantaged ones. However, student use of computers, laptops or tablets available in schools is not widespread and the share of students using these tools has decreased in many countries.

In schools, mere access to and use of computers are not enough to enhance student performance in general topics. The effect of technology on student outcomes depends on how technology is integrated in the classroom and associated with teaching practices. When levels of digital device use at school are very high, student performance is lower in mathematics, reading, science, and even collaborative problem solving. This is because extensive use of new technologies at school may replace other more efficient educational practices or may simply distract students.

Most countries can revisit the way technology is integrated into the curriculum and pedagogical practices. Rather than focusing on specific digital tools or software, a consistent approach is needed at all levels of education that aims to develop digital skills and the complementary skills required to work and live with new technologies,. Decisions to adopt given technologies in schools, for instance, could be better informed by consulting more with teachers to make sure the type of technology fits with their needs, plans and ability to use it.

The teaching profession is a cornerstone of a forward-looking education system

Teachers' ability to use appropriate and innovative pedagogical tools plays an important role in their students' development of the skills they need for the future. Making use of innovative pedagogical tools can also help re-engage students who tend to fail when traditional teaching methods are used or who need more time to learn. Teachers' digital competencies are instrumental for their own students' capacity to make the most out of new technologies. The better teachers' problem-solving skills in technology-rich environments, for example, the better their students' performance in computer problem-solving and computer mathematics (Chapter 5). Problem-solving skills in technology-rich environments do not measure teachers' ability to teach with ICT, but give information on their capacity to use ICT tools and applications to assess, process, evaluate and analyse information in a goal-oriented way.

There is a need to provide high-quality training to teachers on how best to integrate technology in their pedagogical practices. Teachers are less likely than other tertiary-educated graduates to perform well in problem solving in technology-rich environments. In addition, many teachers report needing professional development in ICT skills for teaching. Providing high-quality training for teachers, both initial and continuous, is an important step to ensure education systems adapt to new needs. It can also attract highly skilled and motivated candidates to teaching, which in many countries is not attractive to students.

Lifelong learning for all should become a reality

The rapid pace of change at work and in society brought about by digitalisation requires flexible learning systems. These need to be both lifelong – accessible to all at any age – and life-wide, promoting and recognising learning acquired outside of formal education systems. The term “lifelong learning system” covers the whole range of policies and institutions providing adults with a range of options to continue learning and preparing young people to adapt to changing skills requirements.

Inequalities in learning opportunities tend to start in early childhood education and are reinforced in schools and in higher education. They often continue at later stages of life and in the labour market. For instance, low-skilled workers are more likely to have jobs exposed to the risk of automation and less likely to participate in training. Addressing these inequalities in learning opportunities requires a comprehensive approach. In addition to policies to reduce failures in schools, efforts need to be put on improving the quality of vocational education and training and providing pathways to further education including general programmes. Providing tertiary funding and grants, as well as relevant information on the returns to higher education, can help remove barriers faced by students from disadvantaged backgrounds.

A comprehensive approach is also needed to raise the participation of low-skilled workers in training. Relevant measures include flexible types of learning opportunities, a range of financial and social support for training, and targeted information and guidance to raise awareness of the returns of training. In particular, open education and MOOCs offer new sources of knowledge and skills development throughout life. At this stage, however, they seem to reinforce rather than reduce inequalities in participation in adult learning.

Policies also need to raise the quality of education and training opportunities throughout life. For initial education, this means adapting the school curriculum to changing skills requirements and training the teaching profession to face these changes. For adult education and training, it is vital to ensure that programmes respond to labour market needs at the country and local levels, to set standards for non-formal education and training, and to assess it better.

Better recognition and signalling of skills acquired throughout life would help employers recruit the right person and provide individuals with incentives to continue learning. Online certification of a broad range of skills has developed. Governments can build on this trend to adapt systems of recognition and certification of skills to changing needs.

A range of policies, with skills-related policies being an important element, can address the geographical dimension of digitalisation

Technological improvements and globalisation have led to marked changes in regional and urban performances in advanced economies. In particular, the decline in manufacturing employment and the adoption of digital technologies since the 1980s has contributed to a strong geographical polarisation as jobs are destroyed in some places, while new jobs are created in others. Areas initially well-supplied with high-skilled workers have predominantly benefited from these changes, as high-skilled individuals attracted technology-intensive firms and high-paying jobs, which in turn further attract high-skilled workers. Other areas are left behind, unable to benefit from these developments. The accumulation of disadvantages in some regions has created strong feelings of discontent and injustice among their populations.

As skills beget skills in the digital age, it is important that all areas are able to provide high-quality education at all levels. Effective early childhood education is crucial to narrow skills gaps that emerge at an early age between children of different socio-economic backgrounds but also of different geographical locations. Disparities between regions in students' performance in secondary education also need to be addressed. Across OECD countries, 15-year-old students in city schools score 30 points higher in science than students in rural areas, the equivalent of roughly one academic year. Policies should also tackle disparities in educational aspirations between young people who live more or less near universities, by limiting information gaps, providing distance-based financial aid, and supporting efficient role model and mentoring initiatives.

Higher education institutions can play a significant role in regional convergence. They can increase the demand for and supply of high-skilled individuals through entrepreneurial ventures necessitating proximity to frontier research. They also enable skilled individuals to be more mobile geographically, reducing income gaps and unused productive capacity in declining areas. However, higher education institutions are very unequally distributed within countries.

Labour mobility between geographical areas can lessen the differences in regional performance brought about by digitalisation. Yet, it has been in decline in some OECD countries. Moving from low-income to high-income areas increases labour supply in the high-income area, putting downward pressure on wages. In the medium run, this decreases income gaps between the two areas. Mobile individuals may also have shorter unemployment spells, as they can take advantage of opportunities in areas that are more dynamic. Moreover, they may find a better match for their skill set, which would improve productivity and potentially yield positive local spill-overs. Geographical mobility can be facilitated by removing inefficient land use regulations, moderating the tax bias towards home ownership, revisiting and possibly harmonising local social transfers, and providing financial assistance to unemployed workers to reduce migration costs.

Investments in digital infrastructure are also essential for participation in the digital economy and the adoption of advanced technologies. These can enable areas with no or slow connectivity to enjoy some of the benefits of digitalisation.

The policy effort needs to be co-ordinated

New technologies offer many "do-it-yourself" options: people can learn, work, find out about their health and do many other activities with a click of the mouse or a tap of the screen. However, this publication shows that if most of the responsibility is left to individuals and firms, the benefits of digital transformation may be shared very unequally. Ensuring people can benefit from new technologies at home and at work and are not left behind requires a comprehensive, co-ordinated policy effort. The package of co-ordinated policies needs simultaneously to promote digitalisation where it increases productivity and well-being and cushion its negative impacts. Skills and education policies are of paramount importance to this package.

A first range of challenges concerns labour markets. All interested parties need to consider how to implement a range of policies that can accompany labour market restructuring through effective training and adequate social protection. It is also crucial to discuss how the cost of these policies can be shared between stakeholders to ensure that inequalities do not increase (OECD, 2019[10]). The policy package should also include measures that can facilitate occupational and geographical mobility (e.g. housing policies, occupational licencing) and can shape the incentives to train and benefit from new opportunities (e.g. tax policies, unemployment insurance). In parallel, research and innovation policies can unlock the potential of digital technologies for economic and social well-being, while regional and local development policies can help spread the benefits of digitisation.

Policies also need to address the impact of new technologies on everyday life and societies more broadly. The emergence of new risks that were not envisaged 15 years ago requires a comprehensive and flexible policy approach. Cyberbullying is often difficult to detect and evidence is still scarce on how excessive exposure to smartphones and tablets affects mental health at various ages. The proliferation of fake news and information manipulation affects the political landscape and how citizens vote. Harmful new practices will certainly emerge in the coming years. Children are particularly exposed to some of these risks. Education institutions and teachers have an important role to play in detecting these problems and in teaching students the values and knowledge they need to avoid these behaviours and make informed choices in a complex world. If the responsibility lies solely on parents, inequalities between children will tend to be exacerbated. Local governments can continue to collaborate with communities and social and cultural institutions to better inform all citizens of the benefits and risks of new technologies.

The policy effort required to make the most of digital transformation is substantial and needs to be efficient and cost-effective. Several countries have put in place strategies to co-ordinate policy concerning the digital transformation. However, few of these digital strategies seem to have the necessary level of government engagement, breadth of policy coverage and concreteness of policy responses. There is no single model of how to design such a policy package and countries need to build on the strengths of their respective institutions.

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Annex 1.A. Scoreboard Indicators

Annex Table 1.A.1. List of indicators considered in the scoreboard on Skills and digitalisation

Category	ID	Indicator	Source
1. Skills to benefit from digitalisation			
Providing the necessary skills to the next generation	1.1	Percentage of students scoring below Level 1 (inclusive) in collaborative problem solving, 2015	OECD (2017[11]), *PISA 2015 Results (Volume V): Collaborative Problem Solving*, Table V.3.1, http://dx.doi.org/10.1787/9789264285521-en
	1.2	Percentage of students scoring below Level 1 (inclusive) in creative problem solving, 2012	OECD (2014[12]), "Student performance in problem solving", in *PISA 2012 Results: Creative Problem Solving (Volume V): Students' Skills in Tackling Real-Life Problems*, Table V.2.1, http://dx.doi.org/10.1787/9789264208070-en
	1.3	Percentage of students scoring strictly below Level 2 in PISA (reading, mathematics, science), 2015	OECD calculations based on OECD (2015[13]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/
A limited share of individuals lacking basic skills	1.4	Percentage of 16-29 scoring below Level 1 (inclusive) in literacy and numeracy and having no computer experience or having failed ICT core, 2012, 2015	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis
	1.5	Percentage of 55-65 scoring below Level 1 (inclusive) in literacy and numeracy and having no computer experience or having failed ICT core, 2012, 2015	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis
A meaningful share of well-rounded individuals	1.6	Percentage of 16-65 scoring at least Level 3 (inclusive) in literacy and numeracy, 2012, 2015	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis
2. Digital exposure			
Everyday exposure and use	2.1	Percentage of 16-65 with no computer experience or who failed ICT core test, 2012, 2015	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis
	2.2	Share of households without Internet due to "lack of skills", 2017	Eurostat (2017[16]), *European Community Survey on ICT Usage in Households and by Individuals*, [isoc_pibi_rni]
	2.3	Share of individuals making a diversified and complex use of Internet, 2016	OECD calculations based on Eurostat (2016[17]), *European Community Survey on ICT Usage in Households and by Individuals*, Chapter 4, Figure 4.16
Labour market exposure	2.4	Median non-routine intensity across all workers	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis,, Chapter 2, Figure 2.17
	2.5	Median intensity of ICT use across all workers	OECD calculations based on OECD Survey of Adult Skills (PIAAC) OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, Chapter 2, Figure 2.17
Workers at risk	2.6	Percentage of employment in occupations at high risk of automation requiring at least moderate training needs to transition to occupations at low or medium risk of automation (lower bound)	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, Chapter 3, Figure 3.13
	2.7	Percentage of workers at "high" risk of automation	Nedelkoska, L. and G. Quintini (2018[6]), "Automation, skills use and training", http://dx.doi.org/10.1787/2e2f4eea-en

Category	ID	Indicator	Source
3. Skills-related policies to make the most of digital transformation			
Effective ICT integration in schools	3.1	Gap in scores in science between students in the third quartile of ICT use and those in the bottom quartile	OECD calculations based on OECD (2015[13]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/, Chapter 5, Figure 5.8
Teachers' preparation and training needs	3.2	Percentage of teachers scoring at least Level 2 (inclusive) in problem solving in technology-rich environments	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, Chapter 5, Figure 5.12
	3.3	Percentage of teachers reporting needing further training in ICT	OECD calculations based on OECD (2014[12]), *TALIS database 2013*, http://www.oecd.org/education/school/talis-2013-results.htm, Chapter 5, Figure 5.18
Lifelong learning systems	3.4	Enrolment rates at the age of 3 (early childhood education and pre-primary education) and at age 5-14, 2015	OECD (2017[18]), *Education at a Glance 2017*, Indicators C1 and C2, https://doi.org/10.1787/19991487
	3.5	Share of adults 35 years and older enrolled in at least post-secondary non-tertiary, (PIAAC)	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis
	3.6	Percentage of adults participating in non-formal and informal learning over the past 12 months (PIAAC)	OECD calculations based on OECD (2012[14]) and OECD (2015[15]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis

Chapter 2. A digital world of work: Transformations of occupations and the implications for skills needs

This chapter analyses how digitalisation modifies the skills needed and tasks performed by workers. Technology can replace workers in routine tasks that are easy to automate and complement workers in more cognitively demanding tasks that require creativity and problem solving. To investigate these links between digitalisation and workers' skills and tasks, this chapter uses a new set of empirical analyses based on the Survey of Adult Skills (PIAAC). To successfully navigate the transition to a digital world of work and thrive in it – workers need not only digital skills but also a broad mix of skills, including cognitive and socio-emotional skills. In technology-related occupations, advanced digital skills are necessary. The chapter also assesses the extent to which digital transformation may affect countries and occupations that are lagging behind.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

Digitalisation profoundly changes the world of work: what people do on the job, how and where they work, the skills they need to remain in employment in a changing world, and the type of career progression they may have. Digital transformation involves many technologies and therefore changes the labour market in many different ways. The use of the Internet by most workers, the possibility of automating an increasing range of tasks and the opportunity to supply skills through online platforms have different implications for workers and require different policy approaches. The effects of digital transformation go beyond manufacturing sectors and traditional high-tech sectors and require much more than ensuring that all or some workers have information and communication technology (ICT) skills.

This chapter examines how digital transformation affects the world of work, with a specific focus on skills. It analyses how new technologies change i) skills requirements, and ii) the use and development of skills. A large part of the analysis has been carried out at the level of occupations, which appears to be the most relevant level for examining the implications of the digital transformation for skills needs, and in turn, for skills-related policies.

Digital transformation changes occupations in three major ways that have implications for skills demand and supply, and for workers:

- New technologies *transform* occupations. Some tasks are automated, others are done differently as technology complements workers in their tasks. Overall, the tasks carried out in each occupation change and therefore, the demand for skills also changes. These changes affect most workers who have to adapt their skills sets.
- New technologies make some occupations *less needed in the economy*. In some occupations, most tasks may be automatable, rendering these occupations more likely to disappear in the future. Workers in these occupations may need to change occupations to remain in employment, which would require them to adapt their skills sets and perhaps acquire new skills and knowledge. While assessments of the risk of automation vary, along with the number of jobs that may disappear, policies are needed that prepare workers for this risk.
- New technologies *create* new occupations and new ways to supply skills to the market. New occupations develop that directly involve new technologies (e.g. big data specialists). Preferences for well-being and leisure may change, leading to the expansion of other occupations (e.g. sport coaches). Online platforms lead to major changes in some sectors but also facilitate self-employment for a broader range of workers. People need to have the skills to benefit from these new work opportunities.

Overall, to make the most of digital transformation, policies need to ensure that workers have and develop the skills to both adapt to changes *within* occupations and navigate *between* occupations. In other words, people need to have the skills to be resilient and mobile.

This chapter discusses the transformations of occupations and their implications for skills needs. Chapter 3 investigates how training policies can facilitate mobility between occupations.

The main findings of this chapter are:

- There are many facets to digital transformation, from the development of robots to the platform economy. They affect workers differently depending on the country, sector and firm they work in. The adoption of new technologies leads to both substitution and complementarity effects. Technology replaces workers in the performance of some tasks that can be automated, such as routine tasks (substitution). Workers use technology, such as ICT tools, to perform their tasks differently and perhaps more efficiently (complementarity).
- Workers need to have the right mix of skills to successfully navigate the transition to the digital world of work, and thrive in it. This mix of skills includes, first, strong general cognitive skills, such as literacy, numeracy and basic ICT skills. It also includes analytical skills and a range of complementary skills such as problem solving, creative and critical thinking, communication skills and a strong ability to continue learning. Working in growing occupations linked to new technologies requires advanced ICT skills such as coding skills.
- This chapter provides a range of evidence supporting the need for a mix of skills, and not only for digital skills, to work in a digital environment:
    - Workers in more digital work environments tend to perform more frequently all the tasks considered in the analysis – managing and communicating, accountancy and selling, and tasks involving advanced numeracy skills. Workers more exposed to digitalisation also make a greater use of general cognitive skills and perform more tasks at work that are related to reading, writing and numeracy.
    - Workers in growing occupations exposed to technology (e.g. software and application developers, database professionals, and ICT support technicians) perform sets of tasks and have levels of skills that are similar to those of workers in other occupations requiring similar education levels, except that they also need advanced ICT skills such as coding.
    - In sectors that are more digital intensive, skills get a wage premium compared with other sectors, but this premium is as big for ICT skills as for numeracy skills or management and communication skills.
- Workers are more likely to maintain their skills in workplaces more exposed to digitalisation. Comparing workers with similar characteristics but differing in terms of the digitalisation of their work environments suggests digital environments help workers to retain problem-solving skills in technology-rich environments while non-digital environments may lead to skill obsolescence. Digital transformation affects sectors and firms differently. It may exacerbate the skills gap and inequalities between workers in sectors and firms (mainly large firms) at the forefront of technology adoption and those in sectors and firms lagging behind.
- Online labour platforms may give workers opportunities to find jobs they would not have had otherwise, but flows have been asymmetric. The United States has been the major hiring country and Asia (South and Southeast Asia) a major provider of services. Social protection and labour rights of workers using these platforms need to be respected. It is important to ensure that i) workers in the "gig economy" also benefit from training opportunities and ii) firms looking for skills through online labour platforms do not consequently neglect investment in training for employees. The development of online labour platforms may require rethinking the

allocation of responsibility for workers' training between platforms, employers and employees.

- Countries will continue to face significant labour market changes that have implications for skills. Among countries covered by the Survey of Adult Skills (PIAAC), a group of countries (Chile, Greece and Turkey) are lagging behind, suggesting their workers are likely to face major changes to their jobs' task-content in the coming years, in particular a substantially greater use of technology, and may not have the skills required to face this transformation. Conversely, other countries (Denmark, Sweden and the Netherlands) are ahead in the digital transformation of the workplace, with most of their workers intensively using ICTs on the job and predominantly performing non-routine tasks.
- Low-skilled occupations such as services and sales workers, plant machine operators, or elementary occupations exhibit considerable variation among workers in their exposure to digitalisation, according to the two considered indicators. In some of these occupations, machines may take over the performance of routine tasks. In other occupations, workers who do not currently use computers may be required to start using them. The nature of these low-skilled occupations may therefore change. Workers in these occupations will have to adapt their skills mix to changing needs. In contrast, for high-skilled occupations such as managers, professionals or technicians, the exposure to digitalisation differs significantly less from worker to worker, suggesting these occupations will probably experience fewer changes, unless unforeseen technological disruptions emerge.
- To thrive in the digital economy, workers will need more than just ICT skills. They will also need complementary skills, ranging from good literacy and numeracy skills to the socio-emotional skills required to work collaboratively and flexibly. As a result, a first policy implication is to ensure all individuals acquire a good level of skills proficiency in initial education so they can develop these skills further over their lifetime as well as learn new skills along the way. Reducing the share of young people leaving education with low basic skills becomes increasingly important in a digital world of work. In addition, vocational education and training programmes need to continue to develop general cognitive skills in addition to job-related specific skills. University programmes need to enable students to develop a broader set of skills, including social and emotional skills, in addition to skills related to their fields of study.
- Digital transformation brings with it a crucial need for high-quality and accessible training as skills needs change rapidly. Chapter 3 explores these questions in greater depth.

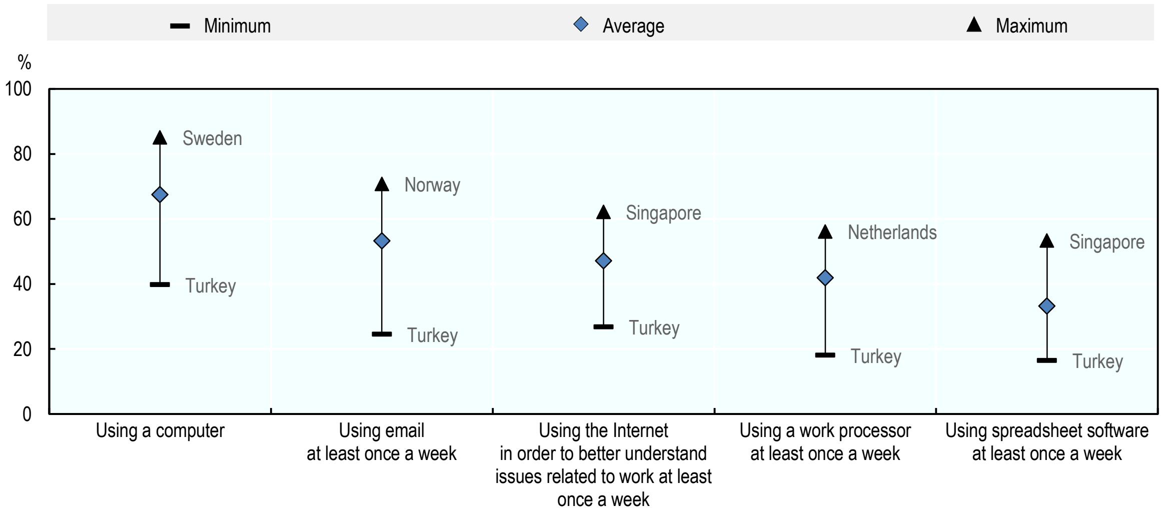
Recent changes in the world of work

Digital transformation affects most workers in OECD countries. Ubiquitous digital devices, connectivity, software and data are profoundly changing the organisation of production, the organisation within firms, what people do on the job and the way they work. An ever-growing share of people will have to work with technology.

In 2015, 57% of European Union workers regularly used a computer or smartphone at work, a surge from 36% only 10 years earlier (Eurofound, 2017[1]). The Survey of Adult Skills (PIAAC), which was administered in 2012 or 2015 depending on countries, also shows that a majority of workers were using a computer (Figure 2.1). However, it shows that large differences existed between countries in the share of workers using the Internet, email and software.

Figure 2.1 Use of computers, the Internet and software at work

Share of workers performing the activity, by country



Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

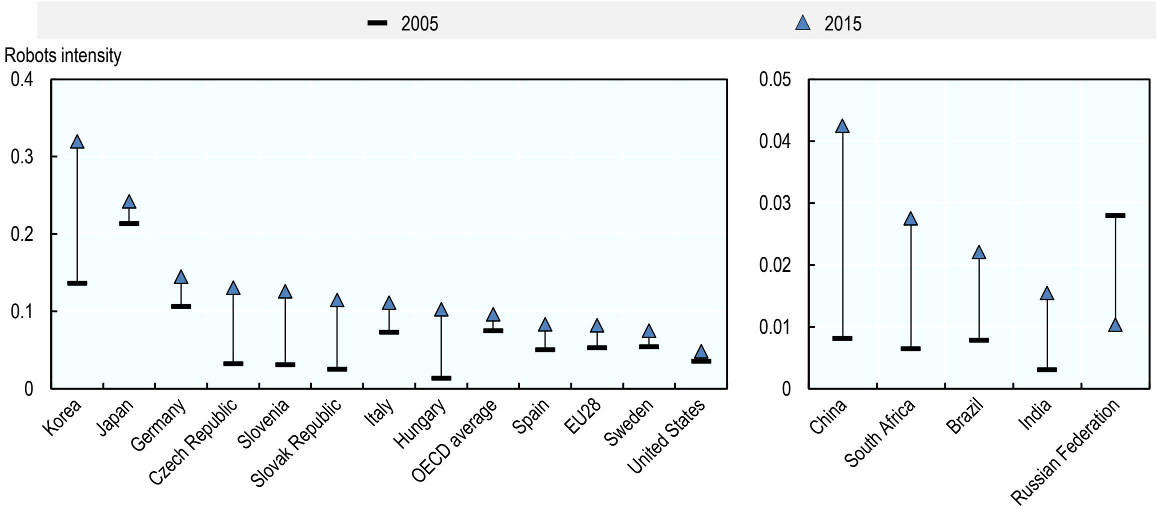
StatLink https://doi.org/10.1787/888933973095

Workers increasingly use technology on the job. Even those who do not use technology may find the nature of their work changing as tasks are increasingly automated. Digitalisation also creates risks that jobs will disappear. Progress in artificial intelligence and machine learning generates possibilities to automate parts of the production process by creating intelligent machines that work, learn and react like humans. The deployment of industrial robots has transformed production processes, particularly in the manufacturing sector, attracting a lot of attention from the media and the public. There are large variations among countries in the use of robots, however, reflecting differences in the adoption of technology (Figure 2.2).

Digital transformation has many facets, which are difficult to summarise in a single indicator. It entails investing in and developing the most advanced "digital" tools, embedding them in production with the help of workers with appropriate skills, and using them when dealing with clients and suppliers (Calvino et al., 2018[3]). When the multidimensional nature of digital transformation is taken into account, it becomes clear that the uptake of digital technologies also differs substantially across sectors (Figure 2.3). Advanced adopters include not only the ICT sector, as one might expect, but also some service sectors such as finance and insurance. In addition, while most firms in the OECD now have access to broadband networks, there are large differences among them in the use of more advanced digital technologies, in particular by SMEs (Andrews, Nicoletti and Timiliotis, 2018[4]).

Figure 2.2. Top robot-intensive economies and BRICS

Industrial robot stock over manufacturing value added, million USD, current values, 2005 and 2015



Note: Robot use collected by the International Federation of Robotics (IFR) is measured as the number of robots purchased by a given country/industry. Robot stock is constructed by taking the initial IFR stock starting value, then adding to it the purchases of robots from subsequent years with a 10% annual depreciation rate. The graph covers all manufacturing, mining and utilities sectors. Data for the following countries is extrapolated for the years 2014 and 2015 due to the lack of data: Australia, Chile, Estonia, Finland, Greece, Iceland, Ireland, Latvia, Lithuania, New Zealand, Norway and Slovenia. Due to lack of available data, the OECD average excludes Canada, Israel, Luxembourg and Mexico. The EU28 average excludes Cyprus and Luxembourg.

Source: OECD (2017[5]), *OECD Science, Technology and Industry Scoreboard 2017: The digital transformation*, http://dx.doi.org/10.1787/9789264268821-en.

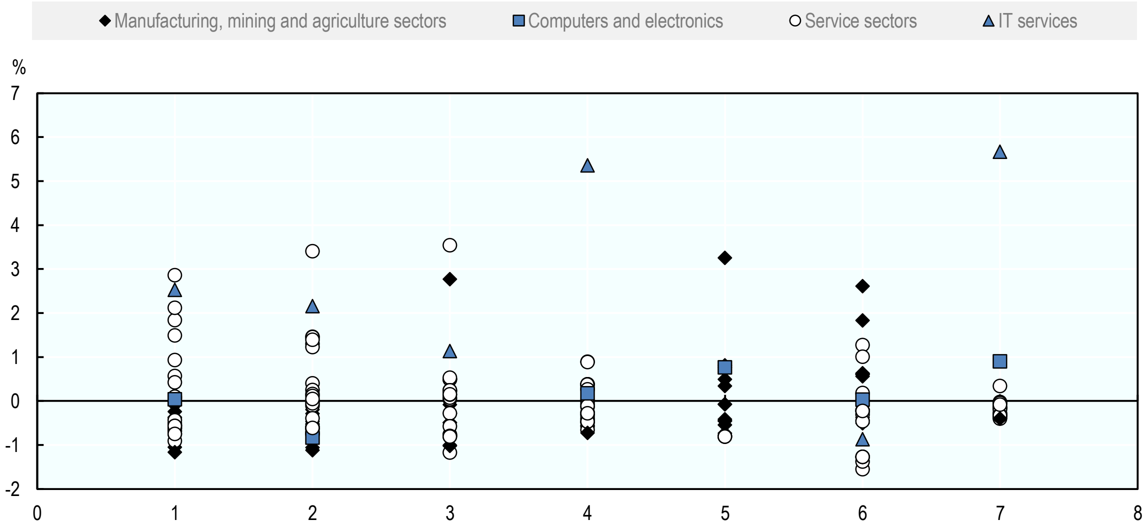
StatLink http://dx.doi.org/10.1787/888933973114

The emergence of online platforms also profoundly changes the world of work. Companies such as Amazon, Facebook, Google and Uber have created online structures that enable a wide range of work activities. Those platforms are diverse in nature and therefore affect labour markets differently. Google is used by many workers to look for information that was more difficult to access in the past. Some platforms (Upwork, Uber) enable anybody to offer their skills in the labour market, often outside standard labour contracts and in addition to other labour activities. People use other platforms to signal skills and create networks (LinkedIn, Facebook). Job-matching sites such as LinkedIn and Monster are changing the way people look for work and the way companies identify and recruit talent.

Digital platforms lead to the reorganisation of a wide range of markets, labour relations and contracts, and ultimately of value creation and capture (Kenney and Zysman, 2016[6]). For instance, Uber has deeply changed the organisation of the taxi industry. The rise of the platform economy raises questions about online workers' social protection and rights, as well as their ability to access and pay for continuing education and training. If the share of workers whose main activity is performed on online platforms increased, the relationship between workers and employers would become more tenuous, reducing employers' involvement in training policies. At the same time, most workers can access online training platforms that provide courses for free (Chapter 4).

Figure 2.3. Dispersion of sectors in each considered dimension of digitalisation

Values averaged across countries and years, and standardised across sectors, 2013-15



Note: All underlying indicators are expressed as sectoral intensities. For each indicator, the sectoral values are averages across countries and years. These values are then standardised relative to the mean, such that the resulting series by indicator have mean zero and standard deviation 1.

Source: OECD (2017[5]), *OECD Science, Technology and Industry Scoreboard 2017: The digital transformation*, http://dx.doi.org/10.1787/9789264268821-en.

StatLink http://dx.doi.org/10.1787/888933973133

Substitution and complementarity between technology and skills: understanding the effects

Technology enables workers to perform some tasks more effectively, complementing their skills. For instance, managers use computer software to organise the work of their team, monitor outcomes, and enhance their collective productivity. Scanners substantially increase cashiers' speed and efficiency. While technology can increase the productivity of both high-skilled and low-skilled workers, it generally favours skilled over unskilled labour by increasing its relative productivity (Acemoglu, 1998[7]; Autor, Katz and Krueger, 1998[8]). New information technologies tend to complement skilled labour, an effect known as skill-biased technological change.

Technology also replaces workers. Computers, software and robots can do routine tasks, such as those involving manual activities (assembling, packing and mail sorting) and those that can be accomplished by following well-defined explicit rules (Autor, Levy and Murnane, 2003[9]).

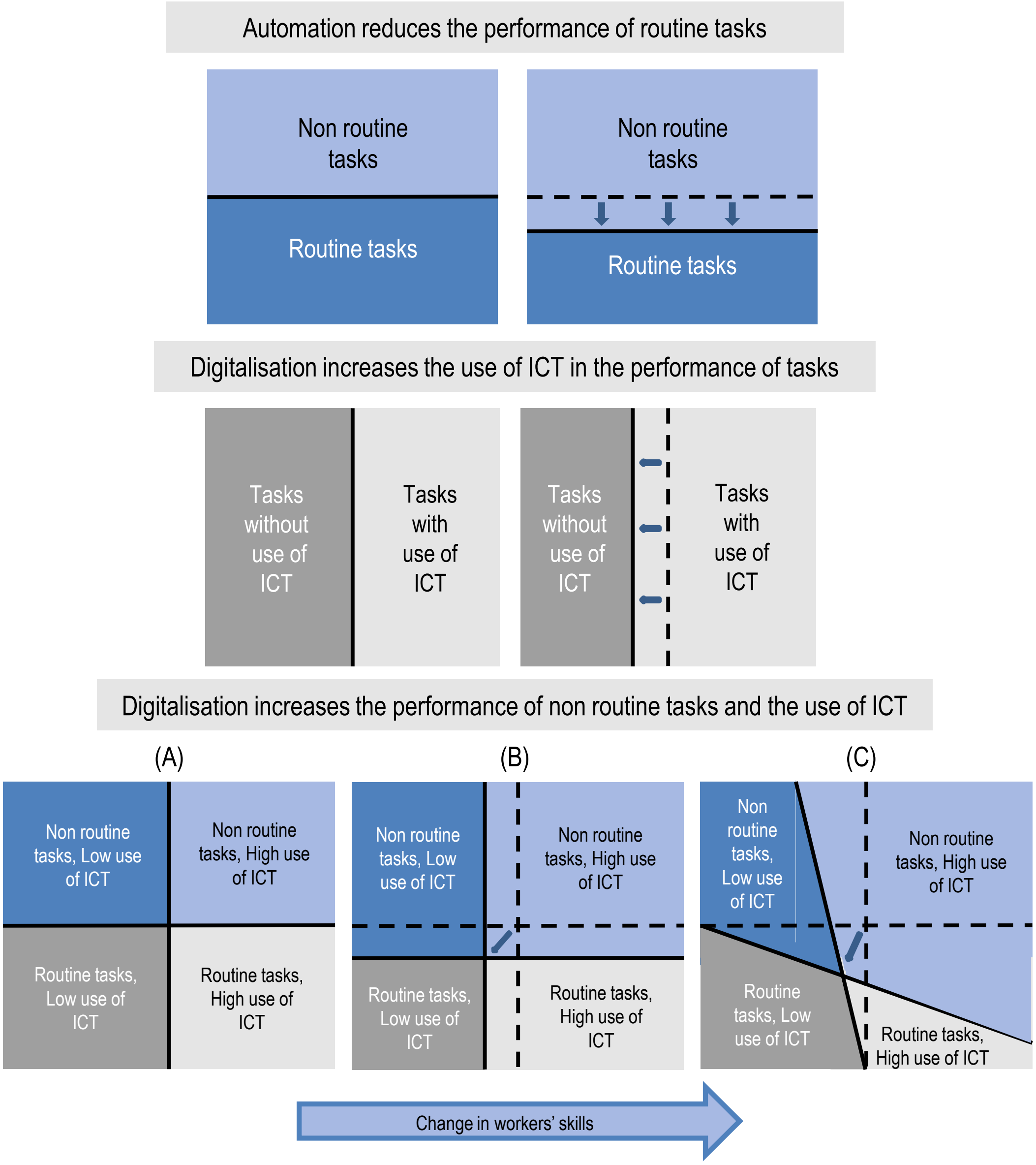
Overall, digitalisation affects workers in two main ways:

- *A complementarity effect*: Technology enables workers to do tasks – such as searching for information or communicating with colleagues or clients – differently and perhaps more efficiently. An increasing share of workers doing problem-solving and communication tasks use ICT tools on the job.

- *A substitution effect*: Technology replaces workers in the performance of some tasks that can be automated. As routine tasks are easier to automate, the substitution effect decreases the routine intensity of jobs.

With digitalisation, workers perform more non-routine, ICT-intensive tasks, and fewer non-routine tasks with no use of technology, as illustrated in Figure 2.4 by the move from (A) to (B). Workers can be complemented by computers in performing routine tasks, though it is likely that these tasks will eventually be wholly automated. Increasingly, computers complement workers in non-routine tasks, while some routine tasks that do not involve ICTs continue to be performed by workers, for instance those involving face-to-face contact. Overall, workers then tend to perform more non-routine, ICT-intensive tasks or routine, non-ICT intensive tasks, as illustrated by the move from (A) to (C).

Figure 2.4. The impact of digitalisation on tasks performed on the job: A framework



Digitalisation of work changes skills requirements and skills development. As some tasks are automated (substitution effect), some skills are needed less while others become more important. As workers use technology (complementarity effect), they work differently, which affects the way they develop their skills. There is a continuous, self-reinforcing dynamic between workers' skills and tasks performed (Heckman and Corbin, 2016[10]; Cavounidis and Lang, 2017[11]). Technology is modifying the sets of tasks that workers perform, and complementing their unique skillsets – but not substituting humans totally (Box 2.1).

Box 2.1. Substitution and complementarity between digitalisation, tasks and skills: Some illustrative examples

Though these are still early days for some of the most advanced technology, such as artificial intelligence (AI), examples ranging from low-skilled to high-skilled occupations suggest that technology has led to both substitution and complementarity effects but is not replacing humans entirely. Rather it is modifying the task composition of workers, and reinforcing and complementing their unique skillset.

Warehouse and production chain workers

Robots have been adopted in many industries, but the most automated systems still tend to lack flexibility. Modern automobile plants, for example, employ industrial robots to install windshields on new vehicles as they move through the assembly line. Yet windshield replacement companies employ technicians rather than robots to change broken windshields. Amazon has automated part of its warehouse and robots handle routine tasks such as moving shelves. However, the firm continues to employ many workers to locate and handle merchandise, and label and ship goods. In many situations, automation is not suitable for a flexible environment, so workers' greater adaptability gives them a comparative advantage over robots.

Cashiers

Since the introduction of self-checkout machines, the role of cashiers has been moving towards assisting customers. Their role can now consist in helping customers properly use the self-checkout machines as well as monitor that the machines are functioning correctly (Andrews, 2009[12]). Cashiers are also redeployed within the store to other tasks such as customer service and sales. However, shops generally continue to offer traditional cashier-staffed checkouts alongside self-checkouts because some people prefer to interact with a human being than with a machine. This societal value attached to human relationships gives workers a new type of comparative advantage over machines, even in low-skilled occupations that technically could be automated. For similar reasons, it is likely that jobs such as nursing or caring for the elderly will remain labour-intensive though these are so far less easily automatable.

Bank tellers

In the United States, the number of automated teller machines has more than quadrupled between 1990 and the 2010s (Bessen, 2016[13]). However, this expansion has not resulted in a decline in the number of bank tellers. Instead, the automation of routine cash-handling tasks has modified the role of bank tellers, who now focus predominantly on fostering customer relationships. Bank tellers are expected to be salespersons rather than checkout clerks (Autor, 2015[14]). The emergence of automated teller machines has changed the content of bank tellers' jobs. Technology substitutes these workers in performing routine tasks, and complements them in the performance of non-routine tasks.

Journalists

Like many professions, journalism has been radically transformed by digitalisation (Örnebring, 2010[15]). In addition to compelling newspapers and magazines to reinvent their business models, technology has altered the practice of journalists themselves. In recent years, sophisticated AI software has been used by newsrooms to automate the writing of stories, to identify breaking news from eyewitnesses, as well as to help journalists in their data-driven reporting (Carlson, 2015[16]). For example, the *Los Angeles Times* uses a computer program named Quakebot to automatically report on earthquakes, *Reuters* employs News Tracer to give an edge to its journalists in identifying breaking news, and *The Washington Post*'s Heliograf has been autonomously writing articles since the 2016 Rio Olympics (Underwood, 2017[17]). Automated journalism is still in its infancy, yet case studies suggest human journalists and "robot journalists" can complement each other: robots can easily report on a multitude of simple events (sports games, polling data, crime, etc.), while humans can focus on creative and detailed stories (Van Dalen, 2012[18]).

Translators

Machine translation has existed for decades. Over the past half-decade, however, advances in various fields of AI, and in particular in artificial neural networks, have vastly improved the accuracy of translating services (Gideon, 2016[19]; Larousserie, 2017[20]). For example, the AI-enabled version of Google Translate launched in late 2016 was able to improve overnight roughly as much as the previous version had over its entire existence (Gideon, 2016[19]). These monumental achievements are likely to significantly disrupt the work of translators, perhaps for the better. As software becomes more precise, translators will be able to rely on it for the first draft and focus on using the special language skills that software lacks (at least for the moment) to improve the style or flow of the translation, identify idioms and translating them accordingly, recognise humour or sarcasm, and ensure it will be understood accordingly.

Lawyers

Some of the tasks performed by lawyers are already being replaced or facilitated by machines (Williams, 2016[21]). Kira, a machine learning-enabled program that analyses legal contracts, "reduces the lawyer time required for contract review by 20 percent to 60 percent", according to the chief executive of the company that produces it (Lohr, 2017[22]). Another program called Ross Intelligence, a legal application of IBM's Watson, can answer legal questions with a two-page memo overnight (Lohr, 2017[22]; Remus and Levy, 2016[23]). As with translators, human lawyers improve upon the machine's first draft. Using data on lawyer time usage in 2014 in large law firms, one study estimated that if all existing technologies were immediately adopted by law firms, the number of hours worked would be reduced by 13% (Remus and Levy, 2016[23]). A more realistic adoption period of five years decreases that number to 2.5% annually. These estimates are small because many tasks undertaken by lawyers require either technical, unstructured knowledge (legal writing, document management) or interpersonal and emotional skills (advising clients, court appearances). The time savings from technology will likely be accompanied by only minor labour savings. Greater productivity from the use of AI-enabled technologies may in fact expand demand for legal advice as costs fall.

Radiologists

Computer-aided diagnosis (CAD) "has become a part of the routine clinical work for detection of breast cancer on mammograms at many screening sites and hospitals in the United States," (Shiraishi et al., 2011[24]). CAD does not replace radiologists or dermatologists in detecting lesions and assessing the extent of the disease, but it does give them a second opinion with which to improve and adjust their initial diagnosis (Deepa and Aruna Devi, 2011[25]; Doi, 2007[26]). This assistance is becoming substantially more reliable with the increasing availability of large medical datasets. On average, a full-time dermatologist might see about 200 000 cases over her career. By contrast, an algorithm based on artificial neural networks built by Stanford researchers could analyse nearly 130 000 cases in three months (Mukherjee, 2017[27]). This algorithm was found to perform on a par with expert dermatologists in detecting skin cancer (Esteva et al., 2017[28]). Algorithms will not be replacing oncologists in the near future, however. Doctors will continue to be needed to understand the conclusions of the program, to evaluate potential causes for the diagnosis, and to interact with patients. Moreover, ethical considerations surrounding the exclusive use of technology cannot be brushed aside easily: who would become liable in the case of an incorrect diagnosis by the machine? The better performance of machines in some diagnoses will likely improve the judgement of radiologists rather than replace them.

Sources: Andrews, C. (2009[12]), *'Do-It-Yourself': Self-checkouts, Supermarkets, and the Self-Service Trend in American Business*, https://drum.lib.umd.edu/handle/1903/9593?show=full (accessed on 03 November 2017); Bessen, J. (2016[13]), "How computer automation affects ocupations: Technology, jobs, and skills", http://dx.doi.org/10.2139/ssrn.2690435; Autor, D. (2015[14]), "Why are there still so many jobs? The history and future of workplace automation", http://dx.doi.org/10.1257/jep.29.3.3; Örnebring, H. (2010[15]), "Technology and journalism-as-labour: Historical perspectives", http://dx.doi.org/10.1177/1464884909350644; Carlson, M. (2015[16]), "The robotic reporter", http://dx.doi.org/10.1080/21670811.2014.976412; Underwood, C. (2017[17]), *Automated Journalism - AI Applications at New York Times, Reuters, and Other Media Giants*, https://www.techemergence.com/automated-journalism-applications/ (accessed on 11 December 2017); Van Dalen, A. (2012[18]), "The algorithms behind the headlines", http://dx.doi.org/10.1080/17512786.2012.667268; Gideon, L. (2016[19]), *The Great A.I. Awakening*, http://dx.doi.org/10.1002/cne.21974; Larousserie, D. (2017[20]), *La traduction dopée par l'intelligence artificielle*, http://www.lemonde.fr/sciences/article/2017/11/27/la-traduction-dopee-par-l-intelligence-artificielle_5221041_1650684.html?xtmc=la_traduction_dopee_par_l_intelligence_artificielle&xtcr=1 (accessed on 12 December 2017); Williams, M. (2016[21]), "'Moneyball for lawyers': How technology will change the practice of law", https://www.lawsocietysa.asn.au/bulletin/BULL_Moneyball_for_lawyers.PDF (accessed on 13 December 2017); Lohr, S. (2017[22]), *A.I. Is Doing Legal Work. But It Won't Replace Lawyers, Yet*, https://www.nytimes.com/2017/03/19/technology/lawyers-artificial-intelligence.html (accessed on 12 December 2017); Remus, D. and F. Levy (2016[23]), "Can robots be lawyers? Computers, lawyers, and the practice of law", http://dx.doi.org/10.2139/ssrn.2701092; Shiraishi, J. et al. (2011[24]), "Computer-aided diagnosis and artificial intelligence in clinical imaging", http://dx.doi.org/10.1053/J.SEMNUCLMED.2011.06.004; Deepa, S. and B. Aruna Devi (2011[25]), "A survey on artificial intelligence approaches for medical image classification", http://52.172.159.94/index.php/indjst/article/view/30291/26223 (accessed on 14 December 2017); Doi, K. (2007[26]), "Computer-aided diagnosis in medical imaging: Historical review, current status and future potential", http://dx.doi.org/10.1016/j.compmedimag.2007.02.002; Mukherjee, S. (2017[27]), *A.I. Versus M.D.*, https://www.newyorker.com/magazine/2017/04/03/ai-versus-md (accessed on 14 December 2017); Esteva, A. et al. (2017[28]), "Dermatologist-level classification of skin cancer with deep neural networks", http://dx.doi.org/10.1038/nature21056.

The way technology enters the workplace is influenced by workers' skills, managerial practices, and several other firm- and industry-specific factors that determine the organisation of work and production, and the capacity to change. Policies that affect the organisation of production play a key role in shaping the adoption of new technologies (Milgrom et al., 1990[29]). It is also important to adopt technology as part of an overall organisation package (Brynjolfsson, Renshaw and Van Alstyne, 1997[30]). Organisational structure, skills and competition have all been suggested as the factors that play the most important role in the adoption of technology (Gallego, Gutierrez and Lee, 2015[31]; Andrews, Nicoletti and Timiliotis, 2018[32])

Policies also have an important influence on the extent to which technology will predominantly substitute or complement workers' skills, and thereby on the impact of digital transformation on employment levels and growth. Investments that complement technology itself include those in skills, in organisational change, in new processes and business models, and also in the intellectual assets that help create value from the new technologies (OECD, 2018[33]).

Up to now, there has been no consensus on the overall impact of digital transformation on employment, because it is difficult to account for the multifaceted aspects of digital transformation and because jobs will be both created and destroyed (Box 2.2). However, there is mounting evidence that it results in considerable restructuring of the labour market, thereby affecting the distribution of jobs, wages and income (OECD, 2018[33]). High-skilled workers have tended to benefit more from technological change as they have skills that complement technology in undertaking non-routine tasks, such as problem solving, or creative and complex communications activities. As a result, over the past two decades the share of employment in high-skilled jobs (and to some extent in low-skilled jobs) has increased in most OECD countries, while the share of employment in middle-skilled jobs has decreased.

In the long term, however, low-skilled workers are most likely to bear the costs of digital transformation. While some high skilled tasks also face a risk of automation, low-skilled workers look most likely to lose their jobs, face increased competition for jobs from middle-skilled workers, are least likely to be able to adapt to new technologies and working practices, and are also least likely to benefit from the new opportunities that arise as a result of digital transformation.

Disparities exist within countries as well as between them, as new jobs appear in places other than where they have been lost. Regions are not equally prepared to face the impact of digital transformation. In countries with important regional differences in skill endowments, fast-growing high-tech firms that create jobs are more likely to be concentrated in high-skilled regions. Low-skilled workers face bigger difficulties finding work in these regions, as they have to compete with more highly skilled workers. These geographic inequalities may exacerbate overall inequalities.

Box 2.2. Assessing the impact of digital transformation on employment

Digital transformation has many facets and involves a range of technologies that affect skills needs and jobs differently. Measuring the impact of digital transformation on employment is difficult. Most studies have focused on automation, which can come not only from the application of AI but also from other types of technologies not necessarily linked to digital transformation. Conversely, AI goes beyond automation as it aims to create intelligent machines that work and react like humans (via machine learning). Digital transformation also includes other aspects – such as online labour platforms and big data analytics – that can have different labour market effects from those coming from the increased automation of tasks.

As a result, the evidence on the net impact of robots and other computer-assisted technologies on employment is mixed (OECD, 2016[34]). For example, though there is a clear direct labour substitution channel, the productivity gains they induce may also expand jobs in the firm or enable the emergence of new productive activities, thereby creating jobs. When these positive effects of digitalisation on employment and wages are factored in, the adoption of robots has been found to lead to a net destruction of jobs in the United States (Acemoglu and Restrepo, 2017[35]) while evidence gathered from several countries points to job losses only for low-skilled workers (Graetz and Michaels, 2018[36]). According to a broader measure of technological change (total factor productivity growth), even when employment falls within an industry as industry-specific productivity increases, that drop is more than offset by positive spillovers to other industries (Autor and Salomons, 2018[37]). Using patent grant texts to identify innovation in the field of automation showed that automation boosted total employment as job growth in the service sector compensated for a fall in manufacturing employment (Mann and Puttmann, 2017[38]).

Sources: OECD (2016[34]), "ICTs and Jobs: Complements or Substitutes?", http://dx.doi.org/10.1787/5jlwnklzplhg-en; Acemoglu, D. and P. Restrepo (2017[35]), "Robots and jobs: Evidence from US labor markets", https://www.nber.org/papers/w23285.ack (accessed on 03 November 2017); Graetz, G. and G. Michaels (2018[36]), "Robots at work", http://dx.doi.org/10.1162/rest_a_00754; Autor, D. and A. Salomons (2018[37]), "Is automation labor-displacing? Productivity growth, employment, and the labor share", https://www.brookings.edu/wp-content/uploads/2018/03/1_autorsalomons.pdf (accessed on 04 July 2018); Mann, K. and L. Puttmann (2017[38]), "Benign effects of automation: New evidence from patent texts", http://dx.doi.org/10.2139/ssrn.2959584.

Changing skills needs on the job

This and subsequent sections use the Survey of Adult Skills (PIAAC) to analyse how digitalisation changes skills needs on the job. They go beyond the usual distinction between routine and non-routine jobs in order to understand how digitalisation affects skills needs by changing the frequency and combination of tasks performed on the job.

Using PIAAC to assess changes in skills needs at the workplace

PIAAC provides a broad range of information about adults' skills and the tasks they perform on the job, which can be analysed using the framework in Figure 2.4. This information can be used to build two indicators of exposure to digitalisation in the workplace (Box 2.3).

The *intensity of ICT use at work* indicator captures how technology complements workers in accomplishing their tasks. It is computed from the frequency with which workers perform a range of tasks using a computer and the Internet, such as reading and writing emails, or using software or a programming language (Grundke et al., 2017[39]). The *non-routine intensity of jobs* indicator captures how technology substitutes workers in their routine tasks. It is calculated using questions about workers' freedom to change or choose the sequence of their tasks, the way they work, and how they plan and organise their work, which can approximate the performance of non-routine tasks (Marcolin, Miroudot and Squicciarini, 2016[40]).

Identifying the routine content of tasks performed by individuals is challenging as this is mostly unobservable and therefore has to rely on a proxy. PIAAC has information on workers' degree of independence in planning and organising their activities and time as well as their freedom in deciding what to do on the job and in what sequence, which gives an indirect measure of the routine content of tasks performed at an individual level. The analysis also uses the following information (Box 2.3):

- Skills indicators that reflect the frequency with which tasks are performed that involve specific skills (so-called task-based skills indicators): management and communication skills, accountancy and selling skills, and advanced numeracy skills (Table 2.1).
- A measure of "readiness to learn" based on self-assessment information.
- Cognitive skills assessed through tests in three domains: literacy, numeracy and problem solving in technology-rich environments (interchangeably referred to as problem solving or computer skills).

PIAAC, which was administered between 2012 and 2015 depending on the country, cannot capture all aspects of the digitalisation of the world of work. In particular, it does not provide information on new forms of work (e.g. Uber drivers, Deliveroo riders, TaskRabbit handypersons) or on how workers can use and market their skills through platforms and online, or even the new jobs that have emerged since (e.g. social media marketing). These issues are discussed later in the chapter. Moreover, as the survey only includes one point in time for each country, it cannot provide a straightforward indication of how digitalisation changes the world of work over time.

Box 2.3. Methodology: Indicators of digitalisation and other indicators considered in the analysis

The Survey of Adult Skills (PIAAC) tests the cognitive skills of adults along three dimensions: literacy, numeracy and problem solving in technology-rich environments. In addition, the survey measures how often people perform several tasks, including reading, writing, numeracy, ICTs and problem solving, thus partially matching the cognitive skills assessed through the tests. It also includes information on how often workers perform other tasks, such as those related to management, communication, organisation and planning, and physical work. Workers also report on their attitudes towards learning, trust, health and other issues.

Non-routine intensity

The routine/non-routine intensity of jobs is computed following the methodology proposed by Marcolin, Miroudot and Squicciarini (2016[40]). The indicator builds on four questions that capture the extent to which one's job is codifiable and sequentiable: 1) "To what extent can you choose or change the sequence of your tasks?" (sequentiability); 2) "To what extent can you choose or change how you do your work?" (flexibility); 3) "How often does your current job involve planning your own activities?" (planning); and 4) "How often does your current job involve organising your own time?" (self-organisation).

Answers to each question range from 1 to 5 (using a Likert scale of integer values with 1 corresponding to "Not at all" or "Never" and 5 to "To a very high extent" and "Every day" depending on the question). To ensure that an individual answering "Not at all" or "Never" to each question has a score of 0, 1 is subtracted from the answer values (such that they range from 0 to 4). The index of routine/non-routine intensity is calculated as an average of the answers to these four questions. It is close to 0 when the job is routine-intensive and to 1 when the job is non-routine intensive.

ICT intensity at work, and other task-based skills indicators

The ICT intensity of jobs and other task-based skills indicators used in this study were developed in work by Grundke et al. (2017[39]). That study summarised 57 questions of the Survey into six factors that are called task-based skills as they capture the types of tasks workers perform on the job and hence presumably the skills they may develop. These six task-based skills are (Table 2.1):

1. *ICT intensity.* This indicator describes tasks associated with ICT use, from reading and writing emails to using word-processing or spreadsheet software, or a programming language. It is used as one of the indicators of digital exposure.
2. *Self-organisational skills.* This indicator includes questions on the extent of flexibility at work and sequentiability of tasks. As some of these questions are used in the non-routine intensity index, this factor is excluded from the analysis.
3. *Management and communication skills.* This indicator gathers a diverse set of items, from teaching people to planning others' activities. All these activities involve communicating with and managing other people, whether they be co-workers or not.
4. *Accountancy and selling skills.* This indicator includes questions on the performance of tasks such as reading financial statements, calculating costs or budgets, using a calculator, and selling products or services.
5. *Advanced numeracy skills.* This indicator includes questions on the performance of numeric tasks such as using simple algebra or formulas, or using advanced maths or statistics, thus corresponding to tasks that are more complex and less specific than those included in the previous indicator.
6. *Readiness to learn.* This indicator consists of items designed to measure this dimension, such as relating new ideas to real life or enjoying learning new things.

Each task-based skill has a score ranging from 0 to 1 and is calculated at the individual level. A higher score is associated with a higher frequency of performing the underlying tasks on the job. Comparing intensities between workers is subject to the limitation that moving from "Never" to "Less than once a month" does not imply the same change as moving from "At least once a week but not every day" to "Every day".

Sources: Marcolin, L., S. Miroudot and M. Squicciarini (2016[40]), "The Routine Content Of Occupations: New Cross-Country Measures Based On PIAAC", http://dx.doi.org/10.1787/5jm0mq86fljg-en; Grundke, R. et al. (2017[39]); "Skills and global value chains: A characterisation", http://dx.doi.org/10.1787/cdb5de9b-en.

Table 2.1. Indicators of skills involved in the performance of tasks (task-based skills)

List of items from the Survey of Adult Skills (PIAAC) included in task-based skills indicators

Task-based skills indicators	Items included in the construction of the indicator
ICT Skills	Frequency of: Excel use; programming language use; transactions through the Internet (banking, selling/buying); email use; simple Internet use; word use; real-time discussions through ICT computer; reading letters, emails, memos; writing letters, emails, memos; and working physically over long periods. Level of computer use required for the job.
Readiness to learn	I like to get to the bottom of difficult things; If I don't understand something, I look for additional information to make it clearer; When I come across something new, I try to relate it to what I already know; When I hear or read about new ideas, I try to relate them to real-life situations to which they might apply; I like learning new things; I like to figure out how different ideas fit together.
Managing and communication	Frequency of: negotiating with people (outside or inside the firm or organisation); planning activities of others; instructing and teaching people; advising people; persuading or influencing others.
Self-organisation	Extent of own planning of: the task sequences; style of work; speed of work; working hours.
Accountancy and selling	Frequency of: reading financial invoices, bills etc.; calculate prices, costs, budget; using a calculator; client interaction selling a product or a service.
Advanced Numeracy	Frequency of: preparing charts and tables; use simple algebra and formulas; use complex algebra and statistics.

Sources: Grundke, R. et al. (2017[39]); "Skills and global value chains: A characterisation", http://dx.doi.org/10.1787/cdb5de9b-en, based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

How digitalisation changes jobs' task-content and workers' skills needs

Analysing the task composition of workers who are in the same group of occupations (1-digit ISCO-08) but whose digital exposure differs may indicate how digitalisation changes the task-content of jobs. However, workers decide to work in digital or less digital environments depending on their skill level. In addition, the data used does not follow workers over time. As a result, this analysis cannot provide causal estimates of the effect of digitalisation on the range of tasks performed on the job and workers' skills.

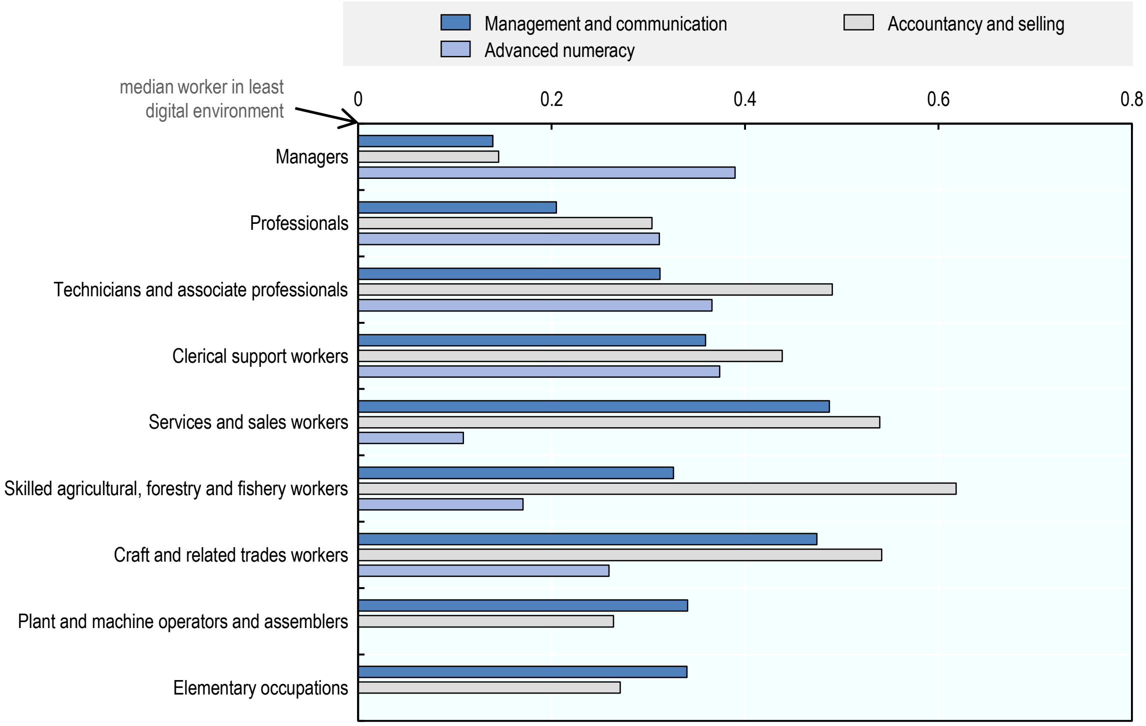
Skills specific to tasks performed on the job

For a given group of occupations, the analysis here assumed that workers in the most digital work environments are those with a non-routine intensity of tasks whose use of ICTs at work is above the median of their group of occupations. Conversely, workers performing more routine tasks and fewer ICT-related tasks than the median of their group of occupations are classified as working in the least digital environments.

Adults working in a digital workplace perform all types of tasks considered in the analysis more frequently than workers in a workplace least exposed to digitalisation. That is, they perform more tasks involving management and communication, accountancy and selling, and advanced numeracy skills (Figure 2.5). This is the case for all groups of occupations considered in the analysis, from elementary to managerial occupations, though for the least skilled jobs there is no increase in advanced numeracy tasks. In more digital environments, managers appear to perform mainly more tasks involving advanced numeracy skills. Workers in elementary occupations perform more tasks involving management and communicating, accountancy and selling skills, while clerks face an increase in the performance of all tasks to the same extent.

Figure 2.5. Job-related skill intensities and digital exposure

Difference in task intensities between workers in most and least digital work environments, by 1-digit occupation



Note: Each bar displays, for each 1-digit occupation, the difference (not percentage change) in task intensity between the median worker in a most digital environment (above median of the 1-digit occupation in both non-routine and ICT intensities) and the median worker in a least digital work environment (below median of the 1-digit occupation in both non-routine and ICT intensities). For example, the median manager's task-content in a most digital work environment is 0.14 more intensive in management and communication tasks, 0.15 more intensive in accountancy and selling tasks, and 0.39 more intensive in advanced numeracy tasks. The construction of the non-routine and ICT intensity and task-based skills indicators is explained in Box 2.3.
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973152

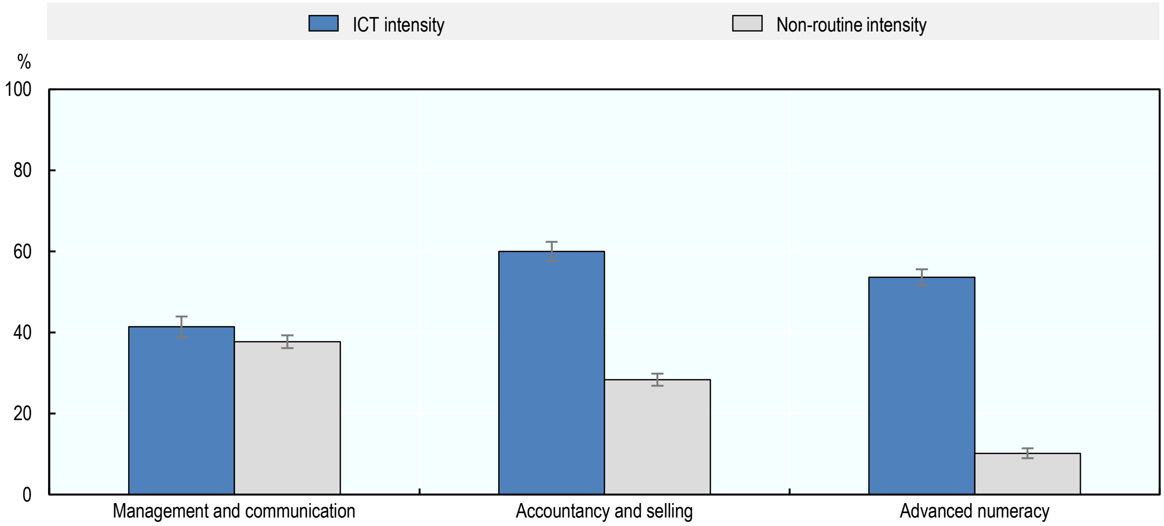
This result, that a range of skills are more frequently involved in an occupation more exposed to digitalisation, holds even when the effect of exposure to digitalisation is separated from other effects by taking into account country, industry and occupation characteristics, as well as age, educational attainment and literacy skills (Figure 2.6).

To put this difference into perspective, if the ICT intensity of workers' professional environment were to increase from the median to the level of the current 75th percentile, they would, on average, perform communication tasks just over 40% more intensively, accountancy tasks close to 60% more intensively, and more advanced numeracy tasks over 50% more intensively. Likewise, when assessing differences with respect to non-routine intensity, if the non-routine intensity of workers' environment were to increase from the median to the 75th percentile, they would, on average, perform communication tasks almost 40% more intensively, accountancy tasks close to 30% more intensively and more advanced numeracy tasks 10% more intensively.

Workers who have more flexibility to plan their work and who make greater use of ICTs perform these specific non-routine tasks more frequently. They mainly do more tasks involving communication and management skills and to some extent more tasks involving accountancy and selling skills. They also perform more tasks involving advanced numeracy, but to a lesser extent, because some less complex tasks involving advanced numeracy skills can be routine cognitive tasks. ICTs tend to be used more mainly for tasks involving accountancy and selling skills, and advanced numeracy skills, and to a lesser extent for tasks involving communication and management skills.

Figure 2.6. Relationship between job-related skills and digital exposure

Expected percentage increase in task-based skills intensities following an increase in digital exposure



Notes: Each bar displays the expected percentage increase in three task-based skills from an increase in the intensity of ICT use at work or in non-routine intensity from the 50th to the 75th percentile. In particular, each task-based skills indicator (management and communication, accountancy and selling, and advanced numeracy) is regressed on the two indicators of digitalisation (ICT and non-routine intensity) and a group of control variables that include occupation, industry, education, age, country, and assessed literacy skills. The error bars represent the 95% confidence interval.
Occupations and industries are included as 1-digit codes of the 2008 International Standard Classification of Occupations (ISCO-08) and 1-digit codes of the International Standard Industrial Classification (ISIC) Rev. 4, respectively. Education is included as six categories from the 1997 International Standard Classification of Education (ISCED). The construction of the non-routine and ICT intensity indicators is explained in Box 2.3.
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973171

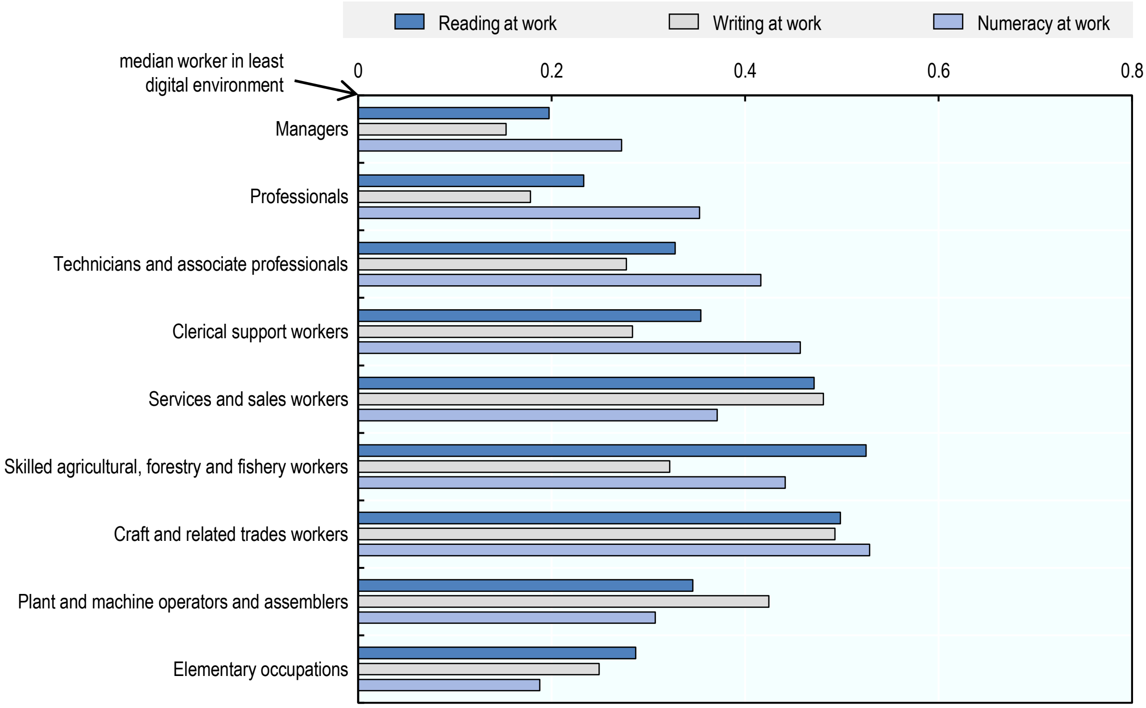
General cognitive skills

Understanding how digitalisation may affect the use of major cognitive skills learned in school, such as reading, writing and numeracy, can help policy makers to improve education policies.

Workers in jobs where ICT use and non-routine tasks are more intensive perform tasks involving reading, writing and numeracy more often (Figure 2.7). Technology complements workers in the performance of tasks like reading and writing emails or using a computer for numeracy tasks. By facilitating the execution of some of these tasks, technology can help workers develop their skills in this area. In addition, as workers perform non-routine tasks more frequently, general cognitive skills are more needed.

Figure 2.7. General cognitive skill intensities and digital exposure

Difference in cognitive task intensities between workers in most and least digital work environments, by 1-digit occupation



Note: Each bar displays, for each 1-digit occupation, the difference (not percentage change) in cognitive task intensities between the median worker in a most digital environment (above median of the 1-digit occupation in both non-routine and ICT intensities) and the median worker in a least digital work environment (below median of the 1-digit occupation in both non-routine and ICT intensities). For example, the median manager's cognitive skill use in a most digital work environment is 0.20 more intensive in reading at work, 0.15 more intensive in writing at work, and 0.27 more intensive in numeracy at work. The construction of the non-routine and ICT intensity indicators is explained in Box 2.3.

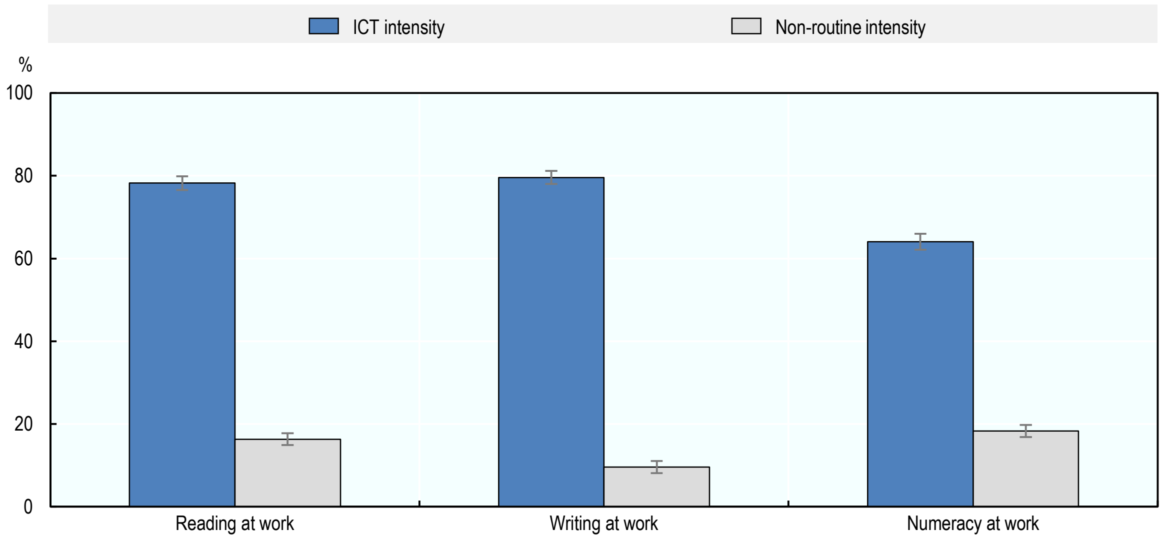
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973190

The importance of this complementarity effect can be assessed by comparing how reading, writing and numeracy skills are used by workers with similar observable characteristics (country, industry, education, age, and assessed literacy skills) and in the same occupation but whose intensity of ICT use is different (Figure 2.8). When the work environment becomes more intensive in non-routine tasks, workers also tend to perform more tasks involving cognitive skills but to a lesser extent than when the use of ICTs increases. The fact that the non-routine intensity of jobs can only be indirectly measured through a range of questions related to the degree of freedom to organise tasks performed may explain why it seems to be less closely related to tasks performed on the job than the use of ICT, which can be captured precisely.

Figure 2.8. Relationship between the use of general cognitive skills and digital exposure

Expected percentage increase in the use of general cognitive skills following an increase in digital exposure



Note: Each bar displays the expected percentage increase in three cognitive skills from an increase in the intensity of ICT use at work or in non-routine intensity from the 50th to the 75th percentile. The same econometric procedure as explained in Figure 2.6's notes is used. The error bars represent the 95% confidence interval.

Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973209

Overall, these results suggest that there are large complementarities between technology and workers. In more digital workplaces, workers make a greater use of cognitive skills in addition to a heightened use of management and communications skills, accountancy and selling skills, and advanced numeracy skills. When workers gain more freedom to plan and organise their work and their work becomes less intensive in routine tasks, they tend to make greater use of communication and management skills, suggesting that social and emotional skills also become more important, as supported by other recent analyses (Deming, 2017[41]).

Learning by doing: The development of skills in a digital workplace

Workers in a digital environment are more likely to maintain or improve the skills they developed during their studies or in past professional experiences, because digitalisation widens the variety of tasks they perform. Conversely, workers who perform specific and technical tasks at work may see the cognitive skills they do not use gradually erode over time and may not develop the social and emotional skills needed. Differences in the task complexity of occupations lead to different learning opportunities (Yamaguchi, 2012[42]). When the value of some skills decreases due to digitalisation, workers invest more in those skills that are more demanded (Cavounidis and Lang, 2017[11]).

How skills evolve with experience

As PIAAC includes only one point in time for each individual, it is not possible to directly observe how skills evolve with experience. However, it is possible to compare the skills of workers who have worked for their employer for the same number of years but whose work environment differs in digital intensity. Such an analysis sheds light on how skills develop with experience, depending on the degree of digitalisation of the workplace.

The analysis includes only individuals who have been working for their current employer for at most 20 years, to increase the likelihood that those whose environment is currently digital also worked in a relatively digital environment when they joined their firm. Self-employed workers were excluded. Crucially, the analysis assumes that the future of individuals who have been with their employers for one year, for example, is proxied by individuals who have been with their employer for longer.

The exposure of the workplace to digitalisation seems to be linked to the development of skills (Figure 2.9). In terms of average problem-solving skills – the interaction between the capacity to use ICT tools and skills to solve problems – the difference between workers in digital and non-digital environments increases with years of experience in that environment. Workers in digital environments are, on average, initially more skilled (in terms of problem-solving skills) than workers in non-digital environments, as evidenced by the difference between the two lines at zero years of experience (i.e. workers who have been with their current employer for less than a year).

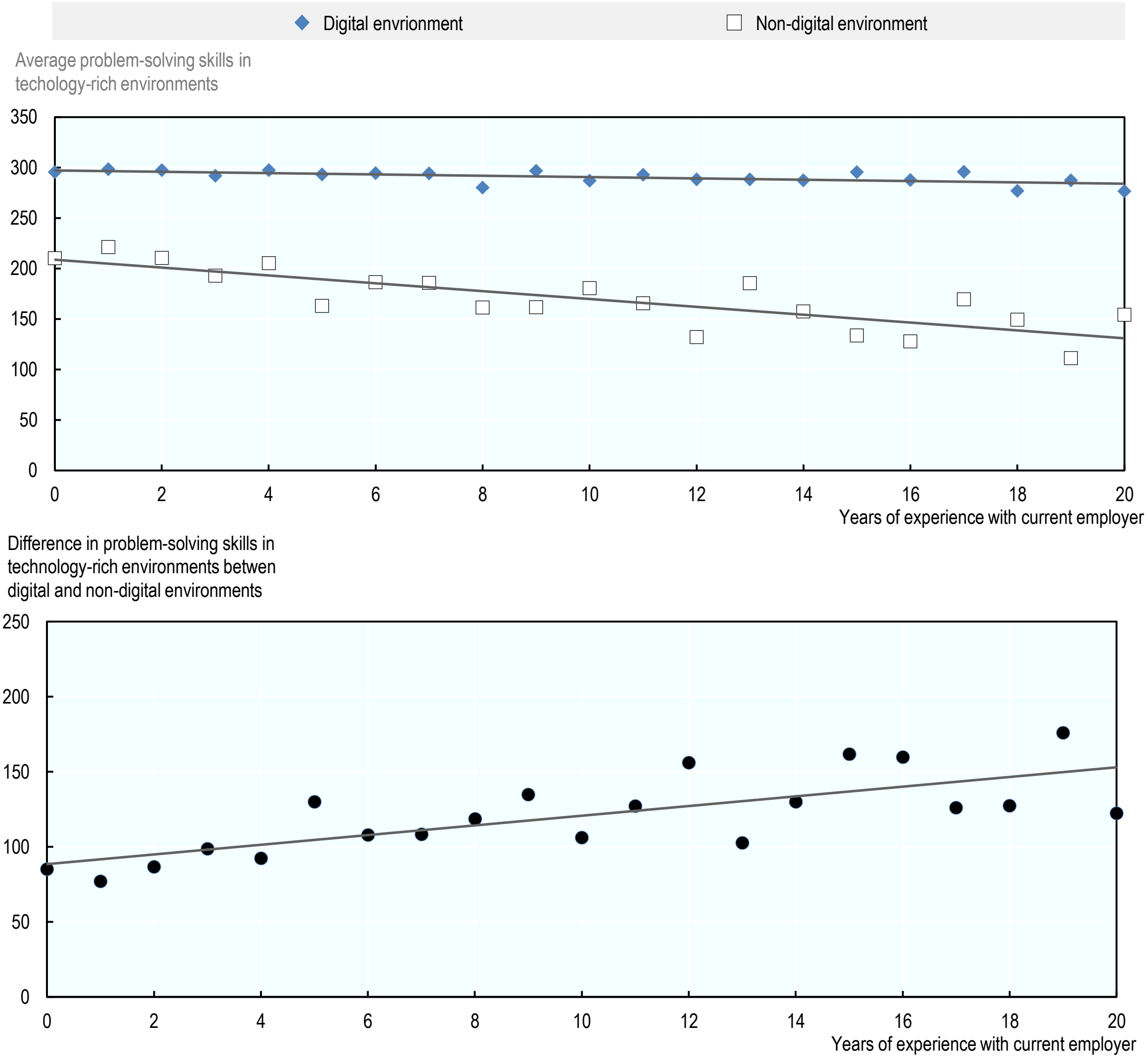
The difference in skills development seems to be driven by skill obsolescence of workers in non-digital environments rather than by upskilling of digitally exposed workers. This could be explained by the fact that workers in digital environments do not necessarily use complex ICT tools. They tend to use simple software (e.g. Excel, Word) very frequently, preventing skill degradation, while a high proportion of workers in non-digital environments do not use any ICTs (18% have no computer experience) leading to rapid decreases in problem-solving skills in technology-rich environments. The depletion of one's proficiency in a particular skill will be greatly affected by the frequency with which one uses the skill in question. ICT skills appear to be particularly subject to obsolescence due to rapid changes both in hardware (smartphones, tablets) and software (more advanced programs, new features) (Cedefop, 2012[43]).

However, these results cannot be interpreted as showing that increasing the digital intensity of workplaces improves skills development. Individuals with better skills and a stronger capacity to adapt are more likely to choose to work in a digital workplace. Likewise, less skilled individuals with a weaker capacity to adapt are more likely to choose to work in a workplace less exposed to digitalisation. To limit this bias (but not fully remove it), several factors that influence workers' choices in terms of workplaces can be accounted for.

The resulting analysis shows that each additional year of experience in a digital work environment is associated, on average, with a 2.2-point increase in workers' problem-solving skills relative to working in a non-digital environment (Figure 2.10).

Figure 2.9. Problem-solving skills development and digital exposure – Descriptive analysis

Average score in problem-solving skills in technology-rich environments of workers in digital and non-digital environments, by years of experience with current employer



Notes: The top panel shows, for each number of years of experience with current employer, the average level of problem-solving skills in technology-rich environments for workers in digital and non-digital work environments. For example, the average level of problem-solving skills in technology-rich environments score of workers who work in a digital environment and have been with their current employer for five years is around 290 while it is around 160 for workers in a non-digital environment. Digital work environments are defined as being above the overall median in both ICT and non-routine intensities. Conversely, non-digital work environments are defined as being below the overall median in both ICT and non-routine intensities. Workers without any computer experience and those who failed the ICT core assessment are assigned a score of 0. Self-employed individuals are excluded from the sample. Both lines represent linear trendlines.

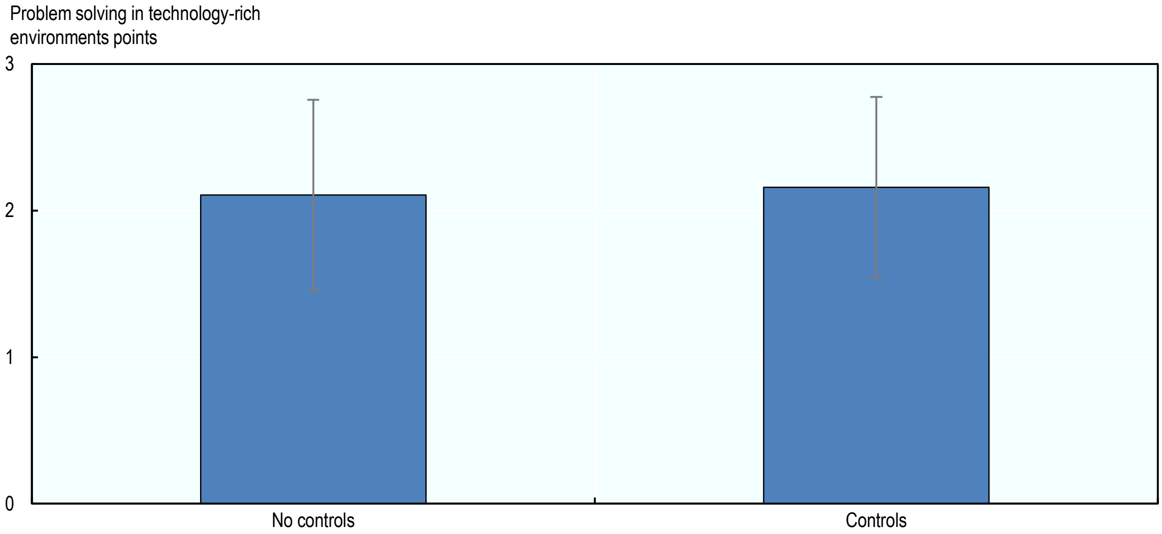
The bottom panel shows the difference, for each number of years of experience with current employer, between the average level of problem-solving skills in technology-rich environments of workers in a digital environment and that of workers in a non-digital work environment. The line represents a linear trendline.

Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973228

Figure 2.10. Problem-solving skills development and digital exposure – Econometric analysis

Expected increase in problem-solving skills for one additional year of experience in a digital environment relative to a non-digital environment



Notes: Each bar displays the expected increase in problem solving in technology-rich environments (PSTRE) score following one year of experience in a digital work environment relative to a non-digital one. Digital work environments are defined as those with a greater ICT and non-routine intensities than the overall median while non-digital environments have lower ICT and non-routine intensities than the overall median. Individuals without any computer experience and those who failed the ICT core assessment are assigned a PSTRE score of 0. To obtain the "No controls" estimate, the PSTRE score of individuals is regressed on an interaction between a digital environment dummy and years of experience with current employer, age, age-squared, years of experience with current employer, a digital environment dummy and country fixed effects. The "Controls" estimate includes occupation and industry fixed effects as well as other variables (education level, literacy and numeracy scores and the readiness to learn).

Occupations and industries are included as 1-digit codes of the 2008 International Standard Classification of Occupations and 1-digit codes of the International Standard Industrial Classification Rev. 4, respectively. The sample is restricted to individuals with at most 20 years of experience with their current employer and self-employed individuals are excluded, though the results remain unchanged if these restrictions are loosened. The error bars represent the 95% confidence interval.

Source: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973247

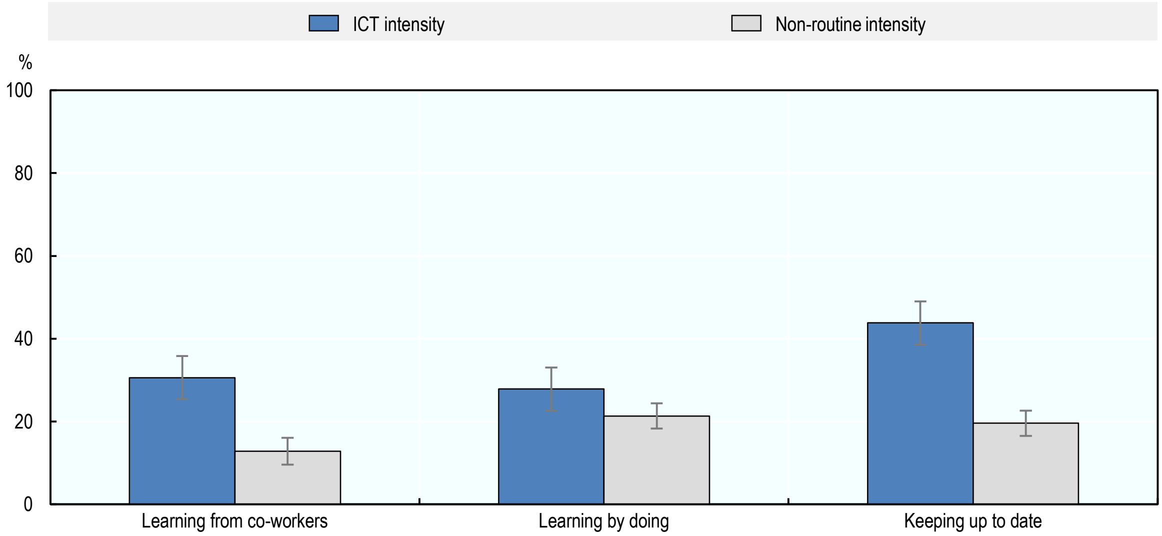
Learning at work and readiness to learn

Workers in digital environments may have greater incentives, preferences and opportunities to develop their skills. As they tend to perform a greater variety of tasks, they are more likely to learn new work-related tools and methods during their careers. Workers who use ICTs more and perform non-routine tasks more often – the two aspects of digitalisation considered in the analysis – tend to learn more from co-workers, learn more by doing and keep up to date more (Figure 2.11). Digitalisation may facilitate the learning process by easing communication within and among teams. As technology changes rapidly, digitalisation also forces workers to keep up to date.

The readiness to learn new things may be one of the most important skills to develop in a rapidly changing working environment. For instance, firms like Google declare they look for "learning animals" while others say they want "people who are intellectually curious" (The Economist, 2017[44]). Readiness to learn or curiosity, just like other skills, can be shaped through education and experience.

Figure 2.11. Relationship between likelihood of learning at work and digital exposure

Expected percentage increase in the frequency of learning at work following an increase in digital exposure



Note: Each bar displays the expected percentage increase in the likelihood of learning from various sources at least once a week from an increase in the intensity of ICT use at work or in non-routine intensity from the 50th to the 75th percentile. The exact same econometric procedure as explained in Figure 2.6's notes is employed. The error bars correspond to associated 95% confidence interval.
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973266

New job opportunities and the implications for skills

New technologies bring many new opportunities for workers, including new or newly growing occupations, and new ways to supply skills to the market. As new products and services emerge, alongside new modes of production and business models, jobs develop not only within high-tech sectors but also outside them. Technologies such as online platforms enable new forms of entrepreneurial activity. These can benefit workers in small businesses, self-employed occupations and others who want to develop activities in addition to their main job. These new ways of working lead to concerns, however, about such workers' social protection. Understanding the type of skills required by these new opportunities is important to ensure that education and training policies help workers and future cohorts of workers benefit from these opportunities.

Skills demanded in growing occupations and growing sectors

Digitalisation creates jobs that did not exist in the past. Examples include applications and systems developers, cloud computing specialists, transport network engineers, medical device consultants, data analysts, and electrical engineers for smart grids. These jobs require workers with a good knowledge of new technologies who are able to complement this knowledge with their own skills, such as communication, problem solving and creativity. Increasingly, workers will have to use technologies on the job to amplify their own skills.

The Survey of Adult Skills (PIAAC) does not capture very recent emerging occupations but does include some occupations that may grow due to digitalisation. Workers in these growing IT occupations can be compared with workers in similar occupations and those who have similar education levels to uncover the skills requirements that seem to differentiate growing occupations from their peers.

Three growing occupations are analysed:

- *Software and applications developers and analysts*. With the ubiquity of personal computers, smartphones and tablets, software and application development often ranks high in people's perception of jobs that have a future. Software and applications developers and analysts include systems analysts, web and multimedia developers, and application programmers.
- *Database and network professionals*. As the amount of data stored by companies and governments has inflated exponentially, so has the need for skills to maintain, secure and facilitate access to this data. Database and network professionals include database designers and administrators as well as computer network professionals. They are likely to be increasingly sought after.
- *ICT operations and user support technicians*. The widespread use of technology (both hardware and software) in numerous areas of life, and especially at work, increases the need for maintenance, installation and assistance to users (whether clients or simply workers in the same firm). ICT operations and user support technicians are key to ensuring the good functioning and appropriate use of technologies within firms and organizations.

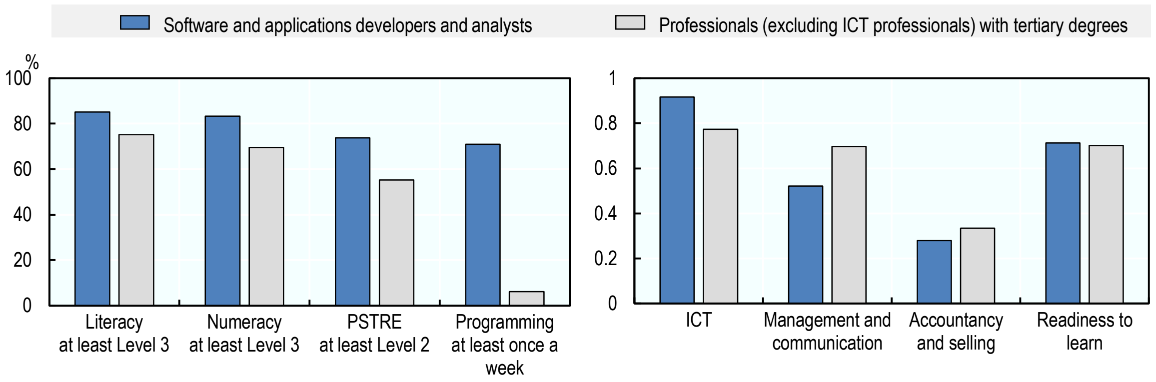
The cognitive skills and task-based skills as well as the frequency of programming of workers in these occupations can be compared with those of workers in similar occupations (other professionals for the first two occupations and technicians for the third) who are not ICT specialists and have a tertiary degree.

Workers in the three growing occupations have slightly higher proficiency in literacy, numeracy and problem-solving skills in technology-rich environments than their peers. They perform ICT tasks slightly more frequently and management and communication tasks less frequently. The biggest difference between the two groups is the frequency of programming: over 70% of software and applications developers, 40% of database and network professionals and 20% of ICT technicians report using a programming language at least once a week, while only about 5% of other professionals or technicians report the same intensity (Figure 2.12).

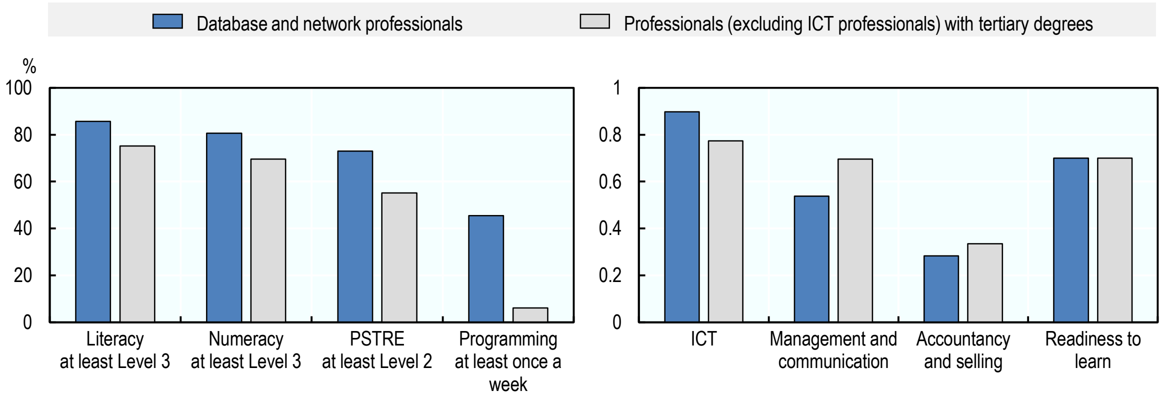
This simple analysis based on specific examples suggests that growing IT occupations require advanced ICT skills coupled with other general cognitive skills and social and emotional skills.

Figure 2.12. Skills mix required in some growing occupations

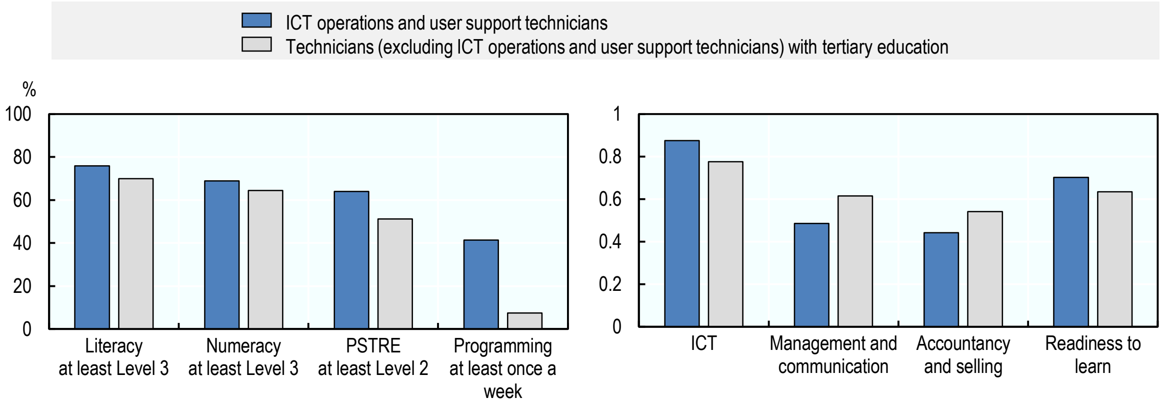
Software developers relative to other tertiary-educated professionals



Database professionals relative to other tertiary-educated professionals



ICT technicians relative to other tertiary-educated technicians



Note: Software and applications developers and analysts and database and network professionals are compared with professionals who are not ICT professionals and who have a tertiary degree. ICT operations and user support technicians are compared with technicians and associate professionals who are not information and communications technicians and who have a tertiary degree. The share of workers who score at least Level 2 in problem-solving skills in technology-rich environments is calculated from the sample excluding workers who opted out of the computer-based assessment, those for whom there is no observation as well as those from France, Italy and Spain. The construction of the task-based skills indicators is explained in Box 2.3.
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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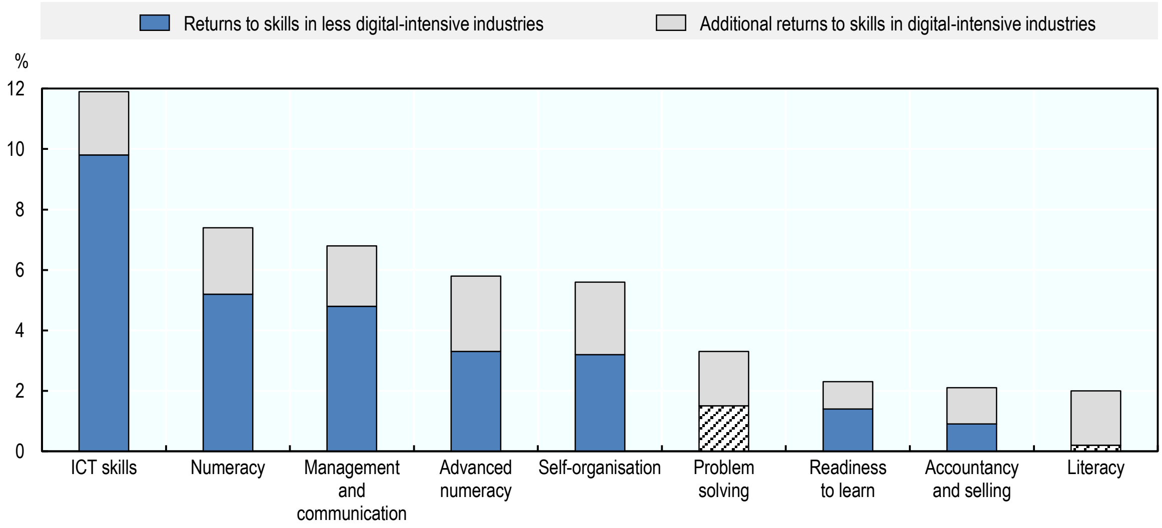
Digital transformation has different effects not only on occupations but also on sectors. As higher wages may reflect relative skills shortages, comparing the wage returns to skills in digital-intensive and less digital-intensive sectors can help explain which skills are more in demand because of digital transformation. In all sectors, wage returns to ICT skills are twice as big as those related to numeracy skills, whereas management and communication skills are rewarded as much as numeracy skills (Figure 2.13). When the many facets of digital transformation are taken into account, skills receive a wage premium in sectors that are more digital intensive. This premium is as big for ICT skills as for numeracy skills or management and communication skills. These findings also provide evidence that ICT skills but also general cognitive skills (such as numeracy) and non-cognitive skills (management and communication) involved in tasks performed on the job are particularly important in digital-intensive sectors.

Figure 2.13. Labour market returns to skills in digital-intensive industries and in less digital-intensive ones

Percentage change in hourly wages for a standard deviation increase in skills



Note: Each bar displays the percentage change in hourly wages for a standard deviation increase in various skills, for both less digital-intensive and more digital-intensive industries. For example, a one standard deviation increase in ICT skills is expected, on average, to yield a 10% and 12% hourly wage increase in less digital-intensive and digital-intensive industries respectively. Digital-intensive sectors are defined according to a range of indicators capturing the multidimensionality of digital transformation: ICT tangible and intangible investment, purchases of ICT goods and services, robot use, revenues from online sales and ICT specialists. The sectors ranking above the median sector by the joint distribution of these indicators are defined as digital intensive. The construction of the task-based skills indicators is explained in Box 2.3. Shaded bars indicate that the result is insignificant at the 5% level.

Source: OECD (2017[5]), *OECD Science, Technology and Industry Scoreboard 2017: The digital transformation*, http://dx.doi.org/10.1787/9789264268821-en.

StatLink http://dx.doi.org/10.1787/888933973304

Online platforms

Online labour platforms have proliferated. They enable anybody to supply labour and skills to the market, in addition to or instead of a standard job. Two major types of platforms exist (Oyer, 2018[45]). In the first group, platforms mediate on-site and in-person services by assigning a provider of services to a buyer of those services, generally for a given price of the service. Examples include Uber, Deliveroo and TaskRabbit. In a second group, freelancing platforms act as a marketplace where sellers of services can connect to buyers of those services from everywhere, with prices negotiated between the parties. Examples include Upwork and Freelancer.

Through these platforms, hiring managers can connect with millions of freelancers around the world (Corporaal and Lehdonvirta, 2017[46]). Small to large firms are using these platforms to access skills and flexible labour. First studies providing data on digital labour platforms are now available (Kässi and Lehdonvirta, 2018[47]; Horton, Kerr and Stanton, 2017[48]). They show that flows have an asymmetric North-South nature. The United States is the major hiring country and South Asia and Southeast Asia are the major providers of services. Except in the United States, flows within countries are limited.

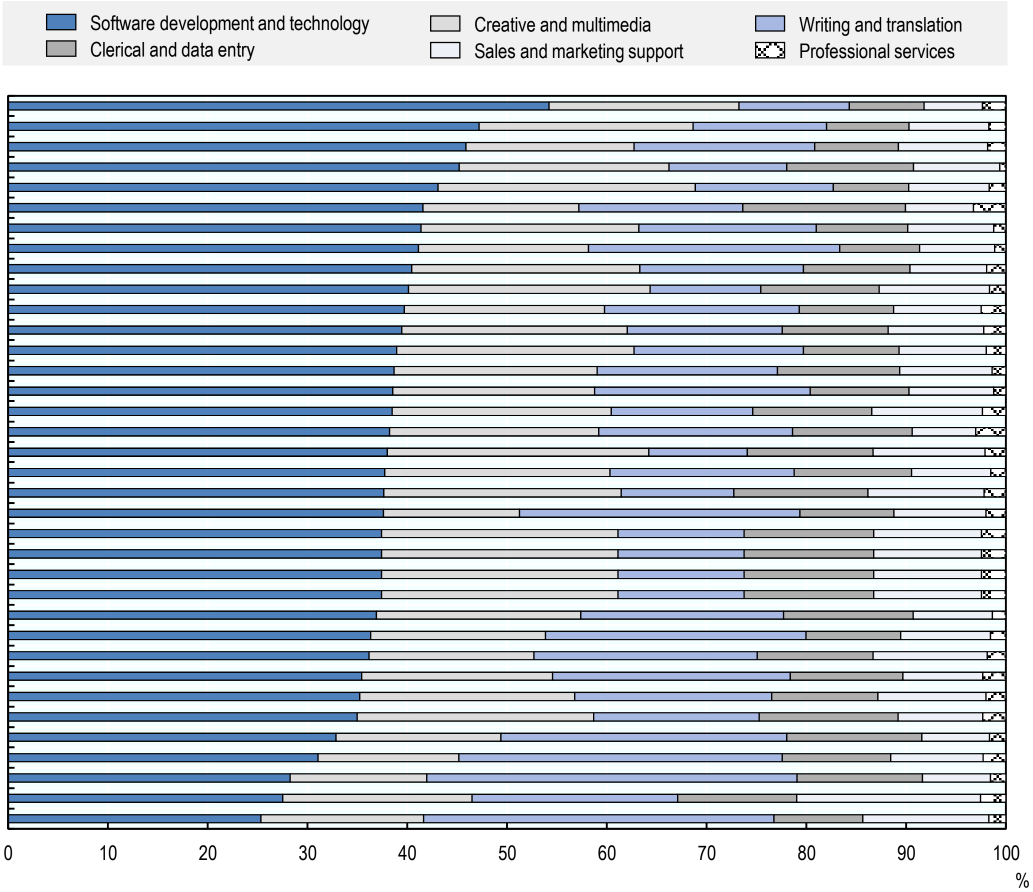
Online labour platforms are mainly used for software development and technology, then for creative and multimedia activities, and then for writing and translation, with differences between countries (Figure 2.14).

Workers using these platforms typically have specific contracts such as contracts with "very short hours" or "on-call" work, including "zero-hours" contracts (with no guaranteed minimum hours). As a result, these platforms are expected to lead to an increase in the share of workers on non-standard forms of contract and more specifically with atypical contracts that are not the same as traditional temporary contracts. There are no comparable data on the extent of these atypical forms of work. In the United Kingdom, 2.5% of employees were on zero-hours contracts at the end of 2015 (ILO, 2016[49]). In the United States, 1.7% of workers worked "on call" in May 2017 and 6.9% were employed as independent contractors, down from 7.4% in February 2005, the last time the survey was taken (U.S. Bureau of Labor Statistics, 2018[50]). Overall, it is not clear at this stage whether these platforms are simply replacing traditional intermediaries in the labour market with digital ones or whether they will lead to large expansions of self-employment and non-standard forms of work.

It is still unclear how these new forms of work will affect workers' skills development and participation in training. The development of online labour platforms exacerbates competition between workers around the world. In particular, it enables firms in OECD countries to call on workers elsewhere with a variety of skill levels, possibly at the expense of investing in the skills of their employees. Evidence suggests that firms using workers on call tend to have a larger share of temporary contracts than other firms and to provide less training (ILO, 2016[49]). Overall, the responsibility of training might shift from firms to individual workers, because firms can look for skills through online labour platforms rather than train their employees and because employees who supply their skills online cannot expect employers to invest in their skills development. At the same time, as work and value creation may become more dispersed with employers playing a smaller role, platform owners increasingly centralise the transactions and may capture their value (Kenney and Zysman, 2016[51]). This raises the question of whether platforms have a responsibility to develop workers' skills.

Figure 2.14. Main skills demanded by OECD countries on the online labour market

Share of project/task occupations by country of employer



Note: Each bar displays employer countries' share of projects/tasks posted on online labour platforms between January and July 2018 by the occupation of project/task. For example, for projects/tasks posted online by employers based in Chile, over 50% of these were related to software development and technology and 20% to creative and multimedia. The Online Labour Index is based on tracking all projects and tasks posted on the five largest English-language platforms, which account for at least 70% of all traffic to online labour platforms. The occupation classification builds on that used by Upwork.com (Kässi and Lehdonvirta, 2018[52]).
Source: Online Labour Index in Kässi, O. and V. Lehdonvirta (2018[47]), *Online Labour Index: Measuring the Online Gig Economy for Policy and Research*, https://mpra.ub.uni-muenchen.de/86627/ (accessed on 20 June 2018).

StatLink http://dx.doi.org/10.1787/888933973323

Within the OECD, online labour platforms may enable workers who can supply services online to find jobs they would not have had otherwise. Therefore, regulations should not prevent these developments. These workers should be covered by social protection and employment policies, however, and have the same incentives and opportunities to participate in training as other workers, while not creating unnecessary new administrative and fiscal burdens. Chapter 6 discusses these aspects further.

The knowns and unknowns about future demand for skills

Some aspects of future demand for skills are predicable. Countries, firms, industries and occupations will progressively adopt existing technologies, albeit at different speeds. The way these technologies have changed demand for and use of skills for countries, industries and firms at the frontier of technology adoption gives an idea of the changes that other countries and occupations may face as they catch up. Other aspects of future demand for skills are much more difficult to predict, because they will depend on future technological developments. They are likely to affect initially countries and occupations that tend to adopt new technology earliest.

The known: catching up effects among countries and occupations

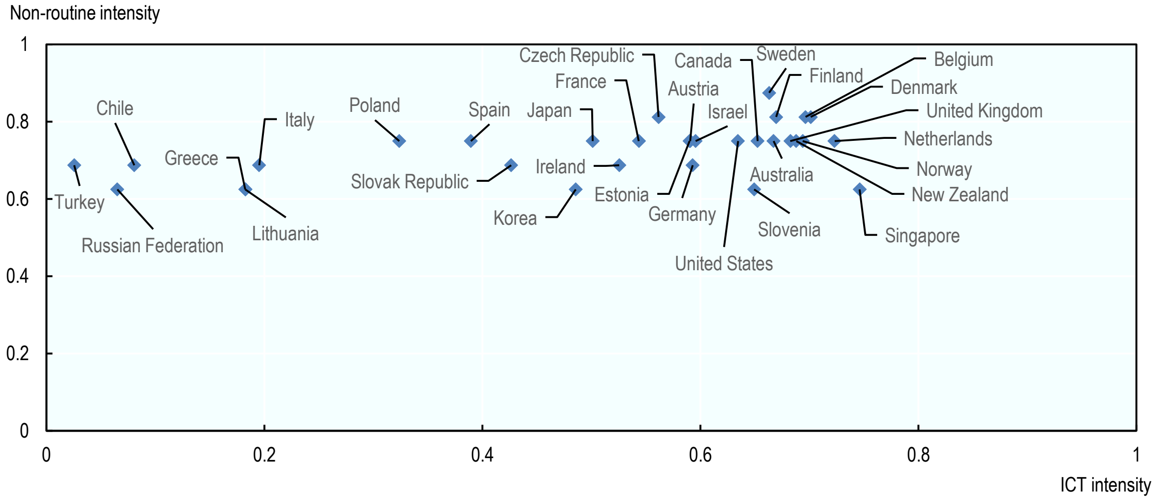
Digitalisation has affected countries, industries and occupations unevenly (Figure 2.4), in ways that may indicate how occupations and, in turn, countries may be affected by digitalisation in the near future.

Variations across countries

Countries have adopted digital tools in the workplace at different speeds (Figure 2.15). A group of countries, including Denmark, the Netherlands, Singapore and Sweden, seems to be well advanced in the digitalisation process, with workers predominantly performing non-routine tasks and using computers intensively. At the other end of the spectrum, Chile, Greece and Turkey are lagging far behind with respect to ICT use at work. The position of countries is not the same for all occupations, but overall, the same countries tend to be well advanced with digitalisation or lag behind.

Figure 2.15. Countries' exposure to digitalisation

Median of the non-routine and ICT intensity indicators across all workers, by country



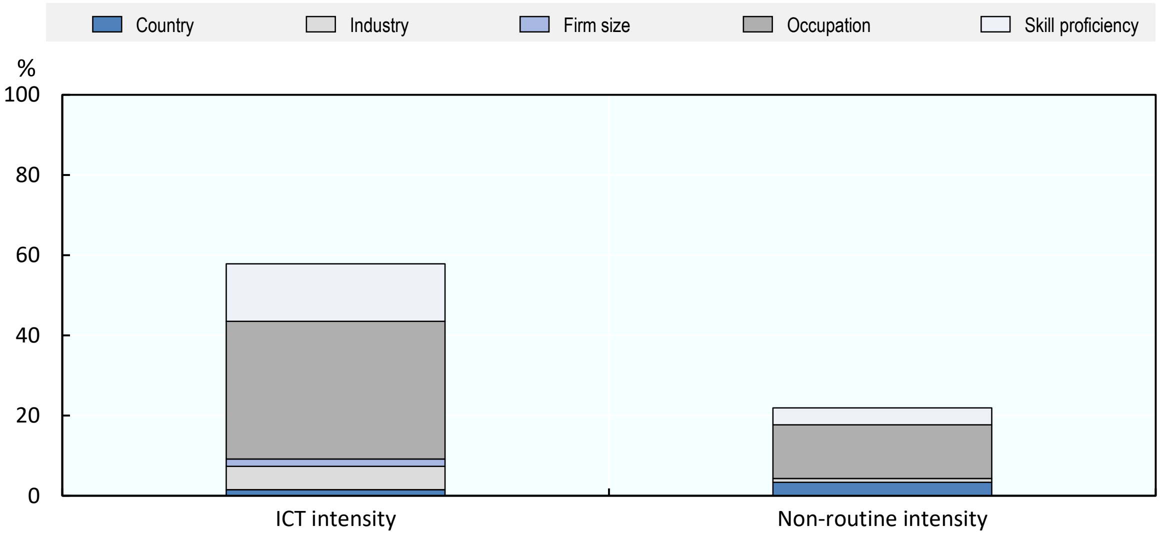
Note: Each dot represents a country's median non-routine and ICT intensities across all workers. The construction of the non-routine and ICT intensity indicators is explained in Box 2.3.
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973342

Countries that lag behind may soon catch up with frontier countries. Yet, differences between countries' digital exposure may also reflect differences in their industrial or occupational structures, such as large differences within a country in digital exposure of occupations or industries. It is possible to assess the extent to which various factors explain the variation in digital exposure between individuals (Figure 2.16). Differences between individuals' intensity of ICT use at work are predominantly explained by differences in the nature of occupations (34%) and by differences in their proficiency in computer skills and literacy (14%), while countries (2%), industries (6%) and firm size (2%) play a minor role. The conclusions are very similar for explaining differences in non-routine intensity, though the factors explain significantly less of its variance. The most important factor that explains differences between workers' exposure to digitalisation is the occupation.

Figure 2.16. The contribution of countries and other factors to the variance of digital exposure

Share of the variance in the digital exposure indicators explained by each factor



Notes: Results obtained using regression-based decompositions proposed by Fields (2003[53]) with one model estimated for each indicator of digital exposure. The height of the bar corresponds to the total R-squared of the full regression model. The subcomponents show the contribution of each factor to the total R-squared. For example, workers' skills explain 14% of the total variance in ICT intensity while their occupation explains 34%.

Occupation and industry are included as 1-digit codes of the 2008 International Standard Classification of Occupations and 1-digit codes of the International Standard Industrial Classification Rev. 4, respectively. Skills proficiency corresponds to literacy proficiency and level of problem solving in technology-rich environments. The construction of the non-routine and ICT intensity indicators is explained in Box 2.3.

Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973361

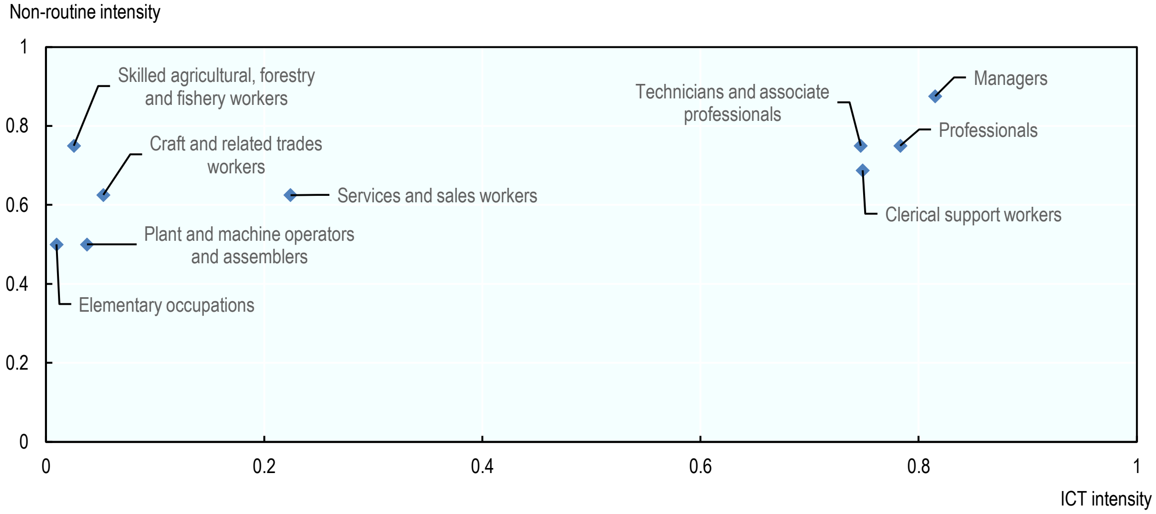
Variations across and within occupations

Occupations differ in their (median) exposure to digitalisation, mostly in their intensity of ICT use but also in their non-routine intensity (Figure 2.17). Unsurprisingly, the most skilled occupations, such as managers and professionals, involve more intensive use of ICT and higher non-routine intensity than less skilled ones. This is consistent with the finding that technology complements high-skilled workers and increases their productivity. Though these occupations are the least prone to substantial changes, new technologies may expand the possibilities of automation, pushing these occupations towards even less routine intensity and greater ICT use.

Conversely, occupations with low ICT use and high routine intensity, such as elementary occupations and plant and machine operators, are most likely to evolve in the near future as automation, industrial robots, computers and artificial intelligence replace workers in performing routine tasks. As a result, adults in these occupations will be increasingly required to perform non-routine tasks and tasks involving ICTs or socio-emotional skills for which they hold a comparative advantage relative to computers. Therefore, it is particularly important to ensure these workers are equipped with the appropriate skill set to adapt to these changes.

Figure 2.17. Occupations' exposure to digitalisation

Median of the non-routine and ICT intensity indicators across all workers, by 1-digit occupation



Note: Each dot represents a 1-digit occupation's median non-routine and ICT intensities across all workers of that group of occupations in all countries. The construction of the non-routine and ICT intensity indicators is explained in Box 2.3.

Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

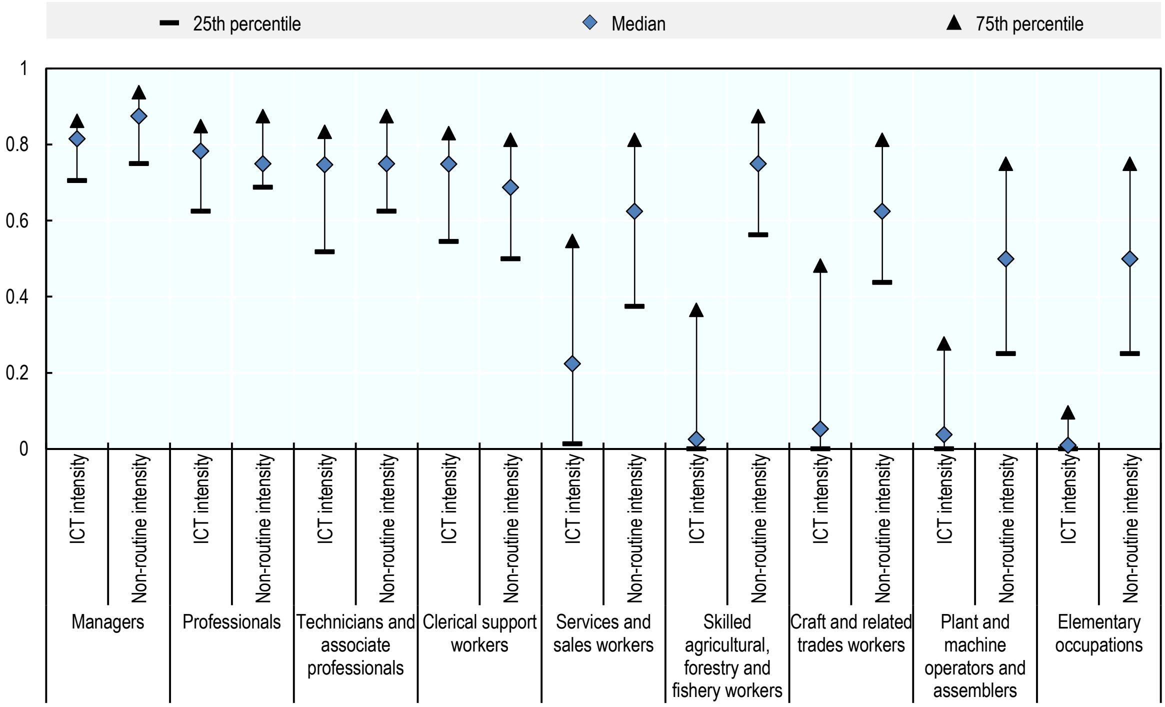
StatLink http://dx.doi.org/10.1787/888933973380

However, even within occupations there is considerable variation in task structure (Spitz-Oener, 2006[54]). Within the same occupation (1-digit), there are large differences between workers of all countries in their use of ICTs and performance of non-routine tasks (Figure 2.18). There are generally smaller variations within high-skilled occupations than within low-skilled ones. This is particularly the case for the non-routine intensity of tasks performed by workers: while there is little variation between occupations for the 75th percentile, low-skilled occupations have a much lower 25th percentile than high-skilled ones. These variations help explain how digitalisation might alter the daily task-content of workers in the near future. Three major scenarios emerge:

- In occupations with the largest proportion of routine, such as elementary occupations and plant and machine operators, workers differ the most in terms of their non-routine intensity and to a lesser extent in terms of their use of ICTs. Workers in these occupations might be mainly affected by a substitution effect, with machines taking over the performance of routine tasks.
- Within some occupations, the variation in the use of ICTs is bigger than in non-routine task intensity, with a large share of workers not using computers at all, such as craft and trade workers, and service and market sale workers. The biggest change for some of these workers might be the introduction and development of technology at their workplace. These workers are also likely to be strongly affected by automation, especially those with high non-routine intensities.
- Finally, skilled occupations such as managers and professionals display small variation in both dimensions, suggesting that the impact of digitalisation on workers in these occupations might be limited, at least in the short term. Other occupations, such as clerks and technicians, show slightly larger variations in these two dimensions, indicating that workers in these occupations will be affected by both a substitution and a complementarity effect.

Figure 2.18. Variation in digital exposure within the same occupation

Non-routine and ICT intensity indicators across all workers, by 1-digit occupation



Note: For each 1-digit occupation, the figure displays the 25th, 50th (median) and 75th percentile of the distribution of the non-routine and ICT intensity indicators across all workers of that group of occupations in all countries. For example, a manager at the 25th percentile has an ICT intensity around 0.7 while it is over 0.85 for a manager at the 75th percentile. The construction of the non-routine and ICT intensity indicators is explained in Box 2.3.
Sources: OECD calculations based on OECD (2012[1]) and OECD (2015[2]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933973399

The unknown: The technology frontier

Countries and occupations at the frontier of technology adoption are also likely to face important changes as new technologies develop. However, there are large uncertainties about the technological capabilities required and the extent to which non-routine tasks could be automated.

Artificial intelligence (AI) is one of the main technologies expected to change the world of work. AI has already several applications today in the transport and health sectors (OECD, 2017[55]). In its current state-of-the-art uses, however, AI is said to be "applied" or "narrow" – designed to accomplish a specific problem-solving or reasoning task. In a hypothetical Artificial General Intelligence scenario, autonomous machines would become capable of general intelligent action, like a human being, including generalising and abstracting learning across different cognitive functions. There are large uncertainties about the time frame for the generalisation of AI that partly depend on advancement of machine learning.

AI may eventually affect a wider range of firms and industries. So far, AI has been mostly adopted by tech firms such as Amazon, Google, and Microsoft, as well as by some start-ups (OECD, 2017[55]). For most firms, AI is still too expensive or too complex to adopt, as they lack the necessary skills. Machine-learning tools based in the cloud are bringing AI to a broader audience, however. These and other technological tools are poised to change the world of work, according to experts (Box 2.4).

Box 2.4. Breakthrough technologies in 2018

Each year, the Massachusetts Institute of Technology lists ten breakthrough technologies (or ranges of technologies) that have not reached widespread use but may have a profound effect on people's lives. In the 2018 list, technologies that could change the world of work include:

3-D metal printing

While this technology is not new, it has remained in the domain of a small group of experts using prototypes and mostly printing objects from plastics. Now the technology has become cheap and easy enough to be integrated in the manufacturing of products. If widely adopted, it could change production, limiting the need for large inventories and making it cheaper to customise products to individual needs.

AI for everybody

For most firms, AI is still too expensive or too complex. Cloud-based AI, which is making the technology cheaper and easier to use, could significantly expand the use of AI by firms and industries. Up to now, AI is used mostly in the tech industry. Other sectors such as medicine, manufacturing, and energy can be transformed if they adopt the technology.

Generative adversarial networks: Advancement in machine learning

The issue of making machines learn how to teach themselves is at the core of much research in the domain of AI. "Generative adversarial networks" are considered a big advance in this direction. The idea is to build on the interactions of two AI systems to achieve an outcome without human intervention. The technology could create ultra-realistic images or sounds that cannot be dissociated from those coming from the real world, for instance. Such technology enlarges the use of AI by making machines less reliant on humans.

Babel-fish earbuds

This technology translates foreign languages in real time. It now works for a large number of languages and is easy to use. In an increasingly global world, language is still a barrier to communication. At work, this technology can give another boost to the globalisation of production.

Source: MIT (2018[56]), *10 Breakthrough Technologies 2018*, https://www.technologyreview.com/lists/technologies/2018/ (accessed on 30 August 2018).

While it is important to understand how technology developments may affect the world of work and skills needs, the technical feasibility of automating a larger range of tasks will not automatically translate into automation of jobs. It will continue to change what workers do on the job, however. Technical feasibility is only one of the factors shaping the future of work. Other major factors include: i) the performance and reliability of future technologies; ii) the cost of technology deployment and adoption relative to the cost of workers and other costs of production; iii) managers and employees' skills and their capacity to work with new technologies. Policies can influence all of these factors.

Summary

Digital transformation includes many facets that profoundly change labour markets. The debate about digitalisation often focuses on jobs at risk of automation and risks that technology will displace workers. In fact, workers in almost all jobs are seeing or will see changes in their work because of digital transformation.

These changes create both challenges and opportunities for workers. Technology can enrich the content of occupations by allowing workers increasingly to focus on non-routine tasks, such as problem solving, creative activities and more complex communications while developing their digital skills by using new technologies. It can also enable workers around the world to bring their skills to the market much more easily through labour market platforms, boosting opportunities for entrepreneurship. On the other hand, workers who lack the necessary skills may find it hard to adapt to change or benefit from new opportunities, and may be left behind.

Because technologies spread to industries, firms and occupations at different paces, workers are affected differently. Workers who are less exposed to digitalisation may be less exposed to job-loss risks in the short term but do not develop the skills they may need to work with new technologies in the longer term. Education and training policies have an important role to play in ensuring that digital transformation does not reinforce inequalities by dividing workers into those who are ICT savvy and those who lag behind.

Education and training policies need to ensure that workers have the right mix of skills to successfully navigate the transition to the digital world of work, and thrive in it. This chapter shows that digital skills are not the same thing as skills for a digital world of work. Even workers in fast-growing, technology-exposed occupations, who need to have advanced ICT skills such as coding, also need strong general cognitive skills, analytical skills and problem-solving skills, as well as social and emotional skills, communication skills and the ability to manage stress and change. Workers in less technologically advanced occupations need to have similar mix of skills but with less advanced ICT skills.

This chapter sheds light on the importance of co-ordinating education and training policies with other policies, an issue discussed further in other chapters. The emergence of labour market platforms raises the issue of the social protection of workers participating in these platforms. Another conclusion of this chapter is the importance for education and training policies to be more forward-looking and to be co-ordinated with the technological trajectory planned by countries. In particular, countries lagging behind in the adoption of new technologies need policies to develop the workforce's skills, co-ordinated with investment in digital infrastructure and research and innovation policies.

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Chapter 3. A digital world of work: Adapting to changes through occupation mobility

The chapter assesses the training needed to make it easier for workers to change occupations and estimates how much it will cost countries to help workers move away from occupations at high risk of automation. To examine the feasibility and cost of occupational mobility, this chapter presents a new set of empirical estimates based on the Survey of Adult Skills (PIAAC). The analysis suggests that with about one year of training, an average worker in most occupations at high risk of automation could move to a low- or medium-risk occupation. The total cost of helping workers in occupations at high risk of automation move away from this risk varies between countries. It may range from less than 0.5% to over 2% of one year's GDP in the lower bound estimate and from 1% to 10% of one year's GDP in the upper bound estimate. However, these costs need not be sustained all at the same time or in one year. These are experimental estimates based on available data. They do not attempt to capture the overall training needed to help all workers face changes in their jobs, but only the training needed for the workers most at risk of losing their jobs. Policies that encourage simultaneous working and learning – through flexible education and training programmes and informal learning – are fundamental to mitigate the cost.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

New technologies, new business models, the dispersal of production in global value chains, the aging of the population and other megatrends are reshaping labour markets. For some occupations, demand is increasing. New occupations are appearing, such as artificial intelligence specialists, bloggers and value chain managers. Demand for others is declining because of digital technologies, automation in particular. An ever-growing number of workers will need to shift from declining occupations to growing ones. In particular, as applications of machine learning and artificial intelligence advance in many sectors, workers will need to move away from occupations that are highly intensive in routine tasks, which can be easily automated.

This chapter investigates how education and training policies can help workers change occupations. After explaining the role of labour mobility for labour market restructuring, the chapter aims to:

1. assess the distance between occupations in terms of skills requirements;
2. identify transitions from any occupation to others that require the least upskilling or (re)training efforts while maintaining workers in quality jobs that make the best use of their skill sets;
3. understand the size and type of (re)training or upskilling efforts needed to help workers move away from occupations at high risk of automation; and
4. assess the monetary cost of the education and training required to move away from the risk of automation.

Finally, this chapter discusses the policy implications of these findings.

As digital transformation affects regions differently, geographical mobility is also important. Chapter 6 discusses these issues.

This chapter uses several concepts to analyse mobility across occupations:

- (Re)training effort: The analysis considers three training needs scenarios: small (up to six months' training), moderate (up to one year) and important (up to three years).
- Possible and acceptable transitions: Possible transitions are those that can happen with a given (re)training effort. Acceptable transitions would entail, in addition, moderate wage reductions and limited skills excesses.
- Risk of automation: The extent to which available technology and potential technical improvement might lead to automation of tasks and jobs.
- "Safe haven": An occupation that a worker can move to with minimum upskilling or (re)training efforts, moderate wage reductions, limited skills excesses and a low or medium risk of automation. Other aspects of the occupation – such as whether it may become less needed in the future for other reasons than automation or its working conditions – are not taken into account.
- Country cluster: – As the full analysis cannot be done at a country level because of data constraints, countries are grouped in clusters.

The analysis in this chapter builds on several assumptions that can affect the size of the effects presented here. The findings should therefore be seen as experimental estimates, intended to foster reflection while indicating policy directions, rather than precise estimates.

The main findings of the chapter are:

- Most occupations appear to be fairly close to some other occupations in terms of cognitive skills requirements, task content, and knowledge area, so most workers have *possible* transitions to other occupations. However, workers may be unwilling to move if moving entails large drops in wages and significant underuse or loss of skills. *Acceptable* transitions, with moderate wage reductions and limited skills excesses, can be identified for just over half of occupations with a small training effort.
- Countries need to invest in education and training to ensure that those at risk of losing their jobs because of automation are not left behind and can find a new job. Many acceptable transitions to occupations at low or medium risk of automation require moderate or important upskilling or (re)training efforts.
- For some workers in occupations at high risk of automation, a small training effort may be sufficient to provide acceptable transitions to occupations at lower risk of automation. Depending on the country cluster, 20% to 50% of occupations at high risk of automation appear to have at least one acceptable transition to an occupation at lower risk of automation that requires at most six months of (re)training. With a moderate (re)training effort (up to one year), these proportions may climb to 65% to 80%. In countries where workers' skills are dispersed, occupations tend to be more distant from one another in their skills requirements and the training effort required to switch occupation is larger. Designing effective options to learn on the job is crucial in these countries.
- Around ten occupations (depending on countries' specificities) are in a particularly critical situation, as they are at high risk of automation and workers in those occupations would on average require an important training effort (more than one year) to move to occupations at low or medium risk of automation. These occupations on average account for 2% to 6% of employment, depending on the country considered. When considering that only a fraction of workers in these occupations are in job at high risk of automation, these figures drop to a range of 0.3% to 1.5%.
- The cost of training includes direct and indirect components. The *direct cost* is the monetary cost of an education and training programme of a given length. The *indirect cost*, or opportunity cost, reflects the wages workers will not receive while they are (re)training. The indirect cost represents 70% of the total training cost per person. This result underlines the importance of enabling individuals to work and learn at the same time, which would lower the indirect cost of switching occupations.
- Estimates of the country-level minimum cost (direct and indirect) of helping workers in occupations at high risk of automation move to "safe haven" occupations vary across countries and depend on the assumption that is made about the number of workers who may need to change occupation:
  - Assuming that only workers who are today in occupations at high risk of automation and perform tasks that can be automated need to change occupation, cost estimates range from less than 0.5% of one year's GDP in Norway to more than 2% of one year's GDP in Chile (lower bound estimate).
  - Assuming that all workers in occupations at high risk of automation need to move, because those occupations are likely to disappear, cost estimates range

from 1% of one year's GDP to 10% of one year's GDP depending on the country (upper bound estimate).

- Differences between countries reflect several factors, including differences in the share of employment in jobs at high risk of automation, the costs of education and training policies, the indirect costs of training, and the occupational and skills distributions of the population.
- The direct country-level minimum cost of moving workers at high risk of automation to "safe haven" occupations is estimated to range from about 3% of secondary and tertiary education yearly expenditure in Belgium to 23% in the Slovak Republic (lower bound estimate).
- These cost ratios may appear high because they compare costs of training that is likely to occur over several years with yearly GDP or education expenditure. Workers and employers may decide to spread training over multiple calendar years to reconcile (part-time) work and training. Furthermore, policies should not target all workers in jobs at high risk of automation at the same time and within one year, as technology spreads and is adopted at different paces in different countries, industries and companies. Lastly, the cost can be shared between the public and private sectors.
- At the same time, these estimates may appear low compared with other public expenditure. This is because they only encompass the cost of education and training policies needed for the workers most at risk of losing their jobs. However, all occupations may change as a result of digital transformation (Chapter 2). The education and training effort necessary to address this broader challenge is larger.
- Specific types of (re)training or upskilling are required to help workers in occupations at high risk of automation move to occupations with lower risk. In addition to training in general cognitive skills, such as literacy and numeracy, these include training in non-cognitive skills, such as management, communications and self-organisation. They also require some training in ICT. This is mainly because occupations at risk of automation include mostly routine tasks, whereas management, communications and self-organisation are more difficult to automate.
- Policies that promote working and learning at the time through flexible education and training programmes and informal learning are fundamental to mitigate training costs and ensure countries can sustain these costs. Furthermore, education systems need to better prepare the next generation of workers for career changes. As well as limiting the number of students who drop out, policies can ensure that vocational education and training programmes include not only job-specific skills but also a strong component of cognitive skills.
- This chapter shows that workers in occupations at high risk of automation are particularly in need of upskilling or (re)training, yet appear less likely to participate in on-the-job training. Policies need to overcome the barriers that prevent some groups of workers from participating in training activities and learning as much as possible on the job.
- As a mix of skills is generally needed to help workers switch occupations, education providers, employers and unions can better co-ordinate their actions to provide the necessary training. At the moment, employers mainly provide training in job-specific skills and few workers go back to formal education in most countries.

- To ensure that inequalities do not increase, everyone involved in labour market restructuring will need to reflect on how to implement a range of policies that share the costs not only of training but also of social protection. Such a comprehensive approach (see Chapter 6) will also need to revisit some specific policy questions, such as which occupations legitimately require a licence rather than a skills certification.
- Uncertainties surrounding estimates in this chapter mainly come from the lack of data on adult education and training programmes, which makes it difficult to assess the cost of these programmes and their returns in terms of skills. More data on adult education and training would enable these programmes to be better designed to meet the needs and constraints that adults face as they continue to develop their skills.

The role of labour mobility

All workers need to adapt to the continuously evolving demand for skills as digital technologies develop and get adopted in different sectors (Chapter 2). Those in occupations at high risk of automation face bigger challenges, however, and need to become more mobile.

Too little occupational mobility when labour markets are restructuring may lead to situations where workers are trapped in declining occupations, risk becoming unemployed or fail to develop their skill sets to adjust to new skills needs. Moving between jobs or occupations entails several costs, however.

Given the nature of digital transformation, moving to a job in a different firm or industry but the same occupation is unlikely to help a worker cope with labour market restructuring. Remaining in an occupation at high risk of automation may merely postpone the redundancy problem rather than solving it, and entail having to move to yet another job in the near future.

An increase in occupational mobility would signal that restructuring of labour markets is indeed taking place, but recent evidence does not point to such an increase (Box 3.1). Studies have found a declining trend in the United States between 1995 and 2015 (Lalé, 2017[1]) and no clear trend in the United Kingdom (Carrillo-Tudela et al., 2016[2]). However, measuring occupation mobility is difficult because of the lack of comparable and reliable data on changes across occupations.

In addition, available studies do not provide clear evidence that workers who are changing occupation move away from the risk of automation. In the United States, the decrease in the share of employment in routine jobs comes from reduced inflows from unemployment to these types of jobs rather than from increased outflows from these jobs (Lalé, 2017[1]). In the United Kingdom, however, career changes tend to move workers from routine to non-routine employment, although these movements did not accelerate during the Great Recession of the late 2000s and early 2010s (Carrillo-Tudela et al., 2016[2]).

The challenge for governments thus becomes helping workers overcome mobility obstacles and fostering smooth transitions in the labour market, while enabling more efficient allocation of workers and skills among occupations, firms and sectors. Of the many policy tools normally used to make mobility easier (e.g. job search assistance through intensive counselling, redeployment benefits or subsidies for geographical relocation), skills policies play an especially important role in the context of digitalisation. Education and training policies can help workers develop the skills they need to adapt to the ever-changing task content of occupations and to move to other jobs when necessary or desired.

It is still not clear how labour markets will be affected by technological development. At the same time, many factors shape workers' opportunities and willingness to change occupations. Policies should therefore not be too specific or try to reallocate workers across occupations on a large scale. Hence, this chapter aims not to be prescriptive but to: 1) inform countries about how they can better design their education and training policies to help workers switch occupations; and 2) provide information on options for occupational mobility and the associated type and size of the necessary investment in training.

Box 3.1. Occupational mobility: What do empirical studies show?

Globalisation and digital transformation are expected to have at least two effects on occupational mobility. First, they trigger labour market restructuring. Some occupations are needed more, while others are needed less, undergo change or disappear. Mobility reflecting structural change in labour demand is generally captured by *net* mobility, that is changes in the shares of employment by occupation. Second, new business models and technologies, including platforms and online employment offers, can help match workers with jobs, thereby reducing excess reallocations or reallocations of workers between occupations that cancel out, leaving the shares of employment by occupation unchanged. Overall, digitalisation could lead to an increase in net mobility and a decrease in excess reallocations.[1]

How many workers change occupation?

Mobility between occupations is difficult to estimate for several reasons. It varies among countries as it is influenced by several labour, housing, social and infrastructure policies and institutions. Job mobility studies are hardly comparable because of data problems. Finally, the estimated mobility depends on the level of aggregation at which occupations are considered. Mobility appears lower at a high level of aggregation (e.g. one-digit level of occupation classifications) than at a detailed level (three or four-digit level of occupation classifications, which also captures changes between occupations within the same aggregated category). Yet there seems to be a consensus that changes in occupations account for almost half of job changes.

Available estimates give the following results for net mobility and for gross mobility, which is the sum of net mobility and excess reallocations:

- In the United States, net reallocations at the 3-digit level of the OCC1990 Classification (387 categories), hence at a detailed level, amounted to 4.4% of employment between 1976 and 2015 (Lalé, 2017[1]). With excess reallocations, i.e. those that cancel out, amounting to 14.6% over the period, gross reallocations reached to be at 19% of employment.

- Between 2011 and 2014, 3% of European workers changed their occupation (capturing gross mobility) per year at a 2-digit level of the ISCO-08 Classification (43 categories) (Bachmann, Bechara and Vonnahme, 2017[3]). Occupational mobility nevertheless differed by country, reaching 7.4% of employment in Sweden, 5.2% in the United Kingdom and less than 2% in France. Net occupation mobility is on average around 2%. Some countries exhibit a very high ratio of gross occupational mobility over net occupational mobility (e.g. Slovak Republic, Hungary and Poland), pointing at excess churning, while the ratio is low for countries such as Greece and Portugal, which suggests that structural changes are occurring in these countries.

- In the United Kingdom – one of the OECD countries with the highest labour market turnover – around 50% of workers who changed job between 1993 and 2012 moved to a new occupation at 1-digit level of the SOC 1990/2000 classification (9 categories) (Carrillo-Tudela et al., 2016[2]). In other words, many workers moved to very different occupations. Likewise, around 50% of workers who changed job took a job in a different industry; workers tended to change occupation and industry at the same time.

Trends in occupational mobility

Occupational mobility shows no clear trend. In the United States, worker net reallocation at the one- and two-digit OCC1990 levels (7 and 80 categories respectively) was stable between 1980 and 2015 (Lalé, 2017[1]). At the 3-digit OCC1990 level (387 categories), an upward trend in the 1980s and early 1990s was reversed between 1995 and 2015. Excess reallocations have increased since 1995. In the United Kingdom, mobility has tended to follow economic cycles (Carrillo-Tudela et al., 2016[2]). Two groups of workers with a higher probability of switching careers are driving occupational change dynamics: those who move voluntarily from job to job, as a change in their career path, and those who get employed after an unemployment spell.

A study found that the difference, or distance, between occupations in terms of their task content is a significant component of the cost of switching occupations (Bachmann, Bechara and Vonnahme, 2017[3]). This suggests a role for task-specific training. Across most occupations, however, only 15% of the total transition costs is attributable to the task distance. This percentage was stable between 1994 and 2013.

Occupational mobility and wages

Mobility is often associated with change in wages. In the United Kingdom between 1993 and 2012, workers in the bottom part of the wage distribution who moved from job to job experienced a fall in real wages of about 15%, while wages fell more than 20% from previous jobs for those coming from an unemployment spell (Carrillo-Tudela et al., 2016[2]). Career changes that involved a step down in skill level were more likely after spells of non-employment. Conversely, those in the top of the wage distribution who changed job experienced a large increase in wages. Such increases were larger for those who changed occupations than for those who changed jobs but remained in the same occupation.

In Europe, only 36% of workers who change their occupation remain in the same earnings decile, which is much lower than for all workers changing jobs (53% with no change) (Bachmann, Bechara and Vonnahme, 2017[3]). Downward transitions can be observed for 37% of occupation changers and upward transitions for 28% of occupation changers. The reason for changing occupation is an important determinant of wage transitions. Workers who change occupation voluntarily have a higher probability of increasing their wages than those who are pushed to change occupation.

Sources: Lalé, E. (2017[1]), "Worker reallocation across occupations: Confronting data with theory", http://dx.doi.org/10.1016/J.LABECO.2016.12.001; Bachmann, R., P. Bechara and C. Vonnahme (2017[3]), "Occupational mobility in Europe: Extent, determinants and consequences", http://dx.doi.org/10.4419/86788852; Carrillo-Tudela, C. et al. (2016[2]), "The extent and cyclicality of career changes: Evidence for the U.K.", http://dx.doi.org/10.1016/J.EUROECOREV.2015.09.008.

The distance between occupations in terms of skills needs

Education and training policies can make it easier for workers to change occupations by helping them develop the necessary skills. Most governments face budget constraints, so it is important that these policies be cost-effective. In particular, policies that help workers move to occupations with similar skills requirements would limit the education and training effort needed. This means it is important to assess the "skills distance" between occupations. A related document explains the methodology used to assess skills distances between occupations (Bechichi et al., 2018[4]).

Methodology: assessing the skills distance between occupations

The Survey of Adult Skills (PIAAC) can be used to assess the distance between occupations in terms of cognitive skills and task content:

1. Literacy and numeracy are used to investigate the extent to which occupations differ in terms of workers' cognitive skills.[2]
2. To evaluate the distance between occupations in terms of their task content, the analysis relies on five "task-based skills" indicators of the frequency with which workers performed tasks involving ICT skills, management and communication skills, accountancy and selling skills, advanced numeracy skills and self-organisation skills (Grundke et al., 2017[5]). The construction of these indicators is explained in Chapter 2 (Box 2.3 and Table 2.1).

Distances between occupations in terms of cognitive skills are more likely to be bridged by formal education and distances in task-based skills through learning on the job, on-the-job training and vocational training.

As a first step, the average requirements in cognitive skills and task-based skills were calculated for the 127 occupations at the 3-digit level of the 2008 International Standard Classification of Occupations (ISCO-08) available in PIAAC. As a second step, multidimensional skill distances between any two occupations, e.g. A and B, were further assessed using measures of skill shortage and skill excess. Assuming a hypothetical move from occupation A to occupation B:

- The measure of skill shortage was computed for all skills for which occupation B required higher levels than occupation A. This showed the type and amount of skills that workers would need to move from occupation A to occupation B. The skill shortage measure was calculated as the weighted sum of the skill differences, with weights mirroring the relative importance of the skills in the destination occupation B.

- The measure of skill excess was computed for all skills for which occupation B required lower levels than occupation A. Thus, the excess measure captures the amount of skills needed to a lesser extent in occupation B than in occupation A.

The shortage and excess measures are symmetric: shortage measures for a move from occupation A to occupation B equal the excess measures for a move from occupation B to occupation A. Box 3.2 explains the detailed methodology.

Occupation distances were computed across all 31 countries included in PIAAC. Due to the size of the PIAAC sample (around 3 500 workers on average by country), distances cannot be computed by country at the detailed occupation level chosen for the analysis. However, it is possible to group countries in clusters according to similarities in terms of the distribution of the tasks performed by workers in each occupation group (Bechichi et al., 2018[4]), and perform this analysis by cluster (Table 3.1). If, for all occupations, workers in the same occupation in a considered cluster perform similar sets of tasks with the similar frequencies, it could be expected that distances between occupations in these countries might be similar.

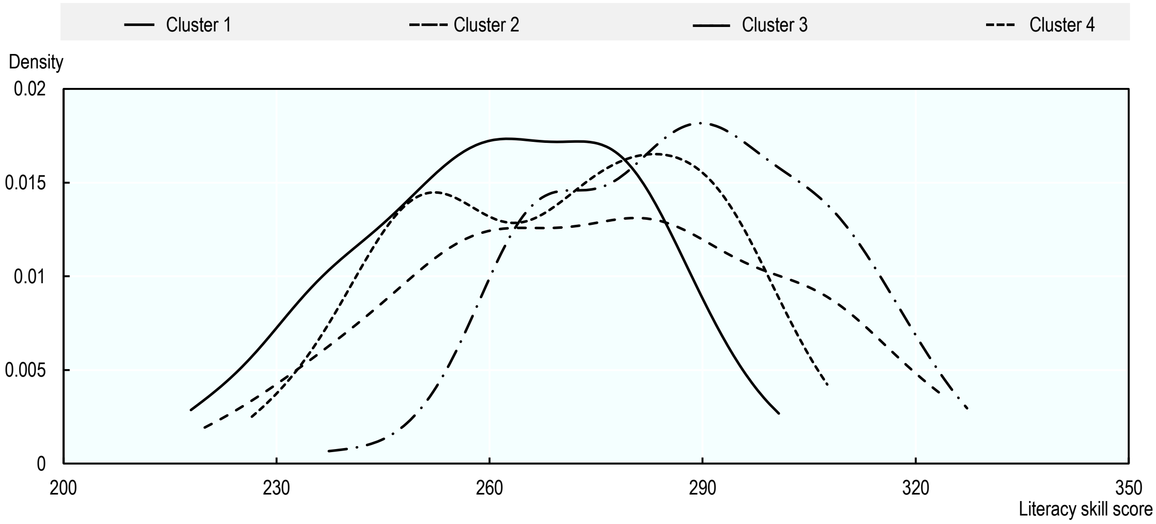
Table 3.1. Grouping of countries according to the cluster analysis

	Countries	Characteristics of skills distribution
Cluster 1	Chile, Greece, Italy, Lithuania, Russian Federation, Slovak Republic, Turkey	Average low skills proficiency; small dispersion
Cluster 2	Australia, Canada, Ireland, New Zealand, United Kingdom, United States	Average medium skill proficiency; large dispersion
Cluster 3	Austria, Belgium, Czech Republic, Denmark, Finland, Germany, Japan, Netherlands, Norway, Sweden	Average high skills proficiency; small dispersion
Cluster 4	Estonia, France, Israel, Korea, Poland, Singapore, Slovenia, Spain	Average medium skill proficiency; medium dispersion

Source: Bechichi, N. et al. (2018[4]), "Moving between jobs: An analysis of occupation distances and skill needs", https://doi.org/10.1787/d35017ee-en.

Clusters of countries differ according to the characteristics of their skills distribution (Figure 3.1). Cluster 1 features countries characterised by low proficiency and a small dispersion. Cluster 2, made up of Anglo-Saxon countries, stands out as having large skills dispersion and medium skills proficiency. Cluster 3 is characterised by the highest skills proficiency and a narrow distribution of skills. Cluster 4 appears similar to what is observed on average across all countries considered.

Figure 3.1. Literacy skills distribution by clusters of countries



Note: Each line represents the kernel density of occupations' average literacy skill in a given cluster. A kernel density can be thought as a smoothed histogram such that approximately, for a given literacy skill score, a greater line height means this literacy skill score is more frequent. That being said, the y-axis cannot be interpreted as actual frequencies. Clusters are defined in Table 3.1.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973418

Box 3.2. Measuring the distance between occupations

Distances between occupations in terms of cognitive skills and task-based skills, as identified in Bechichi et al. (2018[4]), were computed at the three-digit ISCO-08 occupation level using data for 31 countries from the Survey of Adult Skills (PIAAC). Cognitive skills measures rely on the results of two skills assessed through externally administered tests in PIAAC –literacy and numeracy – while task-based skills were computed based on the frequency with which certain tasks are performed by workers following Grundke et al. (2017[5]).

Cognitive skills shortage and excess

Cognitive skills shortage and excess from occupation A to B are defined as the weighted sums of the difference in occupation A and B's average literacy and numeracy skills across countries.

In particular, the shortage is equal to:

$$CogShortage_{A\rightarrow B} =$$

$$\omega_{literacy} \times (literacy_B - literacy_A)\boldsymbol{I}(literacy_B > literacy_A) +$$

$$\omega_{numeracy} \times (numeracy_B - numeracy_A)\boldsymbol{I}(numeracy_B > numeracy_A),$$

where $\omega_{\{literacy,numeracy\}}$ is equal to the relative importance of the cognitive skill in occupation B (e.g. $literacy/\max(literacy, numeracy)$), $literacy_{\{A,B\}}$ and $numeracy_{\{A,B\}}$ are occupation A and B’s average literacy and numeracy skills, and $\boldsymbol{I}()$ is an indicator function returning 1 if the condition in parenthesis is true and 0 otherwise. As such, cognitive skills shortages arise in the case where the origin occupation is insufficiently skilled relative to the destination occupation, in one or both cognitive skills.

Similarly, cognitive skills excess is defined as:

$$CogExcess_{A\to B} =$$

$$\omega_{literacy} \times (literacy_A - literacy_B)\boldsymbol{I}(literacy_A > literacy_B) +$$

$$\omega_{numeracy} \times (numeracy_A - numeracy_B)\boldsymbol{I}(numeracy_A > numeracy_B).$$

Cognitive skills excesses arise when the origin occupation is more skilled in one or both cognitive skills than the destination occupation. Overall, around 47% of possible transitions involve no cognitive skills shortages.

Task-based skills shortage and excess

The task-based skills shortage and excess from occupation A to B are defined as the weighted sums of the difference in occupation A’s and B’s average intensities for five task-based skills: ICT skills, management and communication skills, accounting and selling skills, advanced numeracy skills, and self-organisation skills. They were computed following Grundke et al. (2017[5]). The task-based skills shortage is equal to:

$$TaskShortage_{A\to B} =$$

$$\sum_{t=1}^{5} \omega_t \times (Intensity_B^t - Intensity_A^t)\boldsymbol{I}(Intensity_B^t > Intensity_A^t),$$

where t is one of the five task-based skills, ω_t is equal to the relative importance of task-based skill t in occupation B’s task portfolio, and $Intensity_{\{A,B\}}^t$ is equal to the average intensity of the task-based skill t in occupation A or B.

Similarly, task-based skills excess is defined as:

$$TaskExcess_{A\to B} =$$

$$\sum_{t=1}^{5} \omega_t \times (Intensity_A^t - Intensity_B^t)\boldsymbol{I}(Intensity_A^t > Intensity_B^t),$$

As with cognitive skills, transitions between occupations are likely to involve both shortages and excesses of different skills, unless one of the two occupations requires strictly more of each task-based skill than the other occupation. Overall, around 23% of transitions involve no task-based skills shortages.

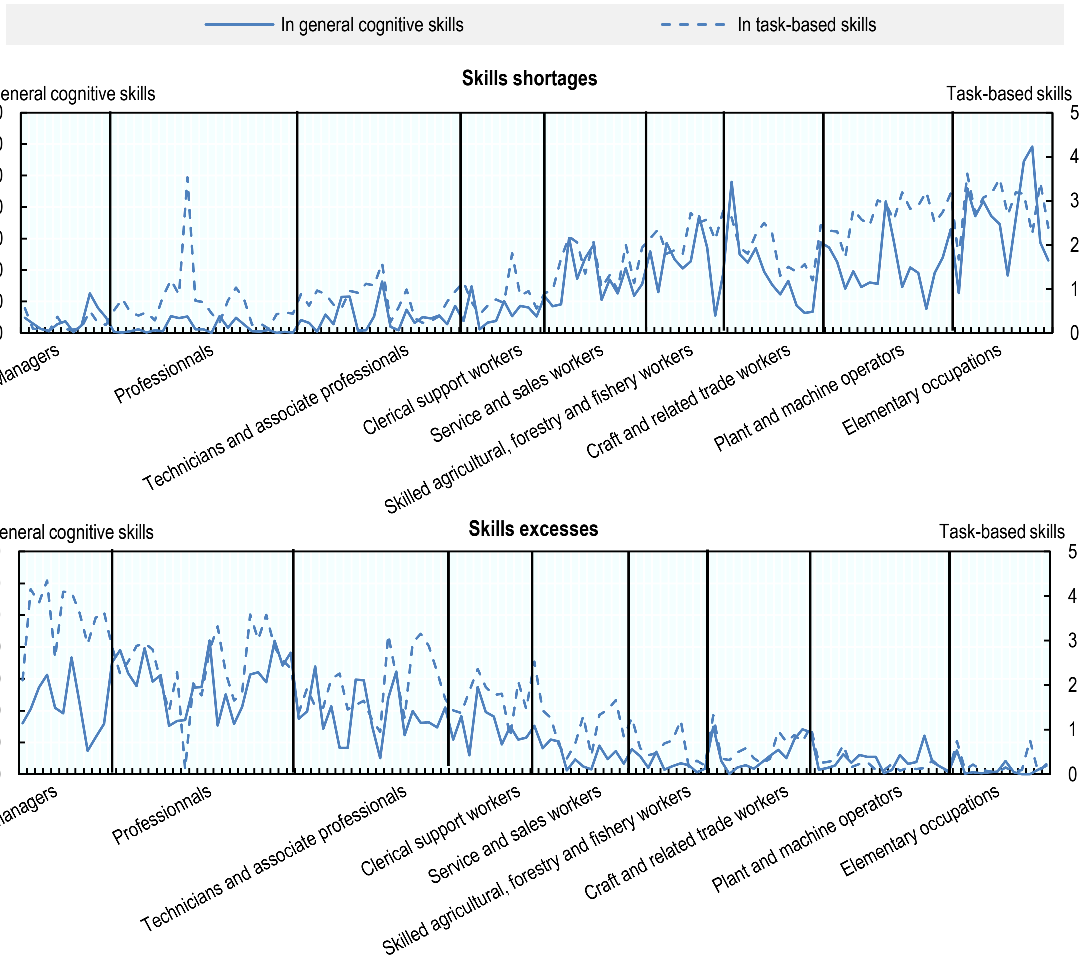
Sources: Bechichi, N. et al. (2018[4]), “Moving between jobs: An analysis of occupation distances and skill needs”, https://doi.org/10.1787/d35017ee-en ; Grundke, R. et al. (2017[5]), “Skills and global value chains: A characterisation”, http://dx.doi.org/10.1787/cdb5de9b-en.

Results: how distant occupations are from one another

Distances between occupations involve both skills shortages and excesses, and this is true for general cognitive skills (literacy and numeracy) and task-based skills (ICT, self-organisation, advanced numeracy, accounting and selling, and managing and communicating) (Figure 3.2). Moves from high-skilled occupations, such as those belonging to managers and professionals, to other occupations would on average entail small shortages and large excesses in both cognitive skills and task-based skills. Conversely, moves from low-skilled to other occupations would on average entail large shortages and small excesses in both cognitive skills and task-based skills. Mobility for middle-skilled occupations to other occupations generally involves both substantial skills shortages and excesses.

Figure 3.2. Average skills shortage to move to other occupations

Average skills shortages to move from one occupation to any other occupation



Note: Each tick mark corresponds to an occupation within the group of occupations mentioned on the axis and indicated by a blue area.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973437

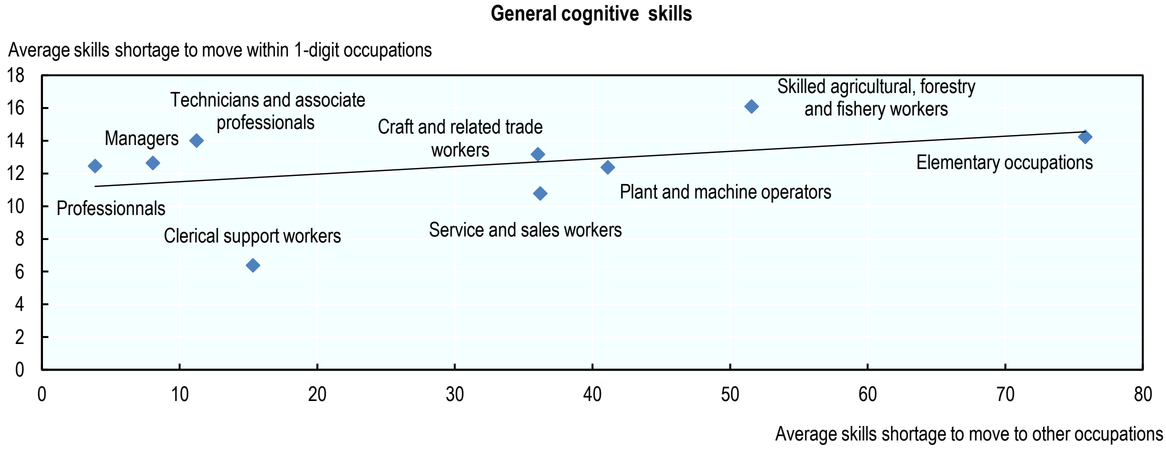
Statistics on distances from one occupation to any other occupation help shed light on the effort that may be needed to move on the labour market. However, workers are more likely to switch to occupations that are closer to their occupation of origin in terms of skills requirements. In particular, transitions within the same (one-digit ISCO-08) group of occupations (e.g. within managerial jobs or elementary occupations) can be considered as "close" transitions, or transitions to similar occupations.

A slightly positive relationship between the average distance to all other occupations and the average distance within the same group of occupations emerges in terms of cognitive skills (top panel of Figure 3.3). This means that close transitions would entail significantly greater shortages in cognitive skills for elementary occupations than for managers. In contrast, distances in terms of task-related skills within the same group of occupations are larger for high-skilled occupations groups such as technicians and professionals than for low-skilled ones such as plant and machine operators, and for elementary occupations (bottom panel of Figure 3.3).

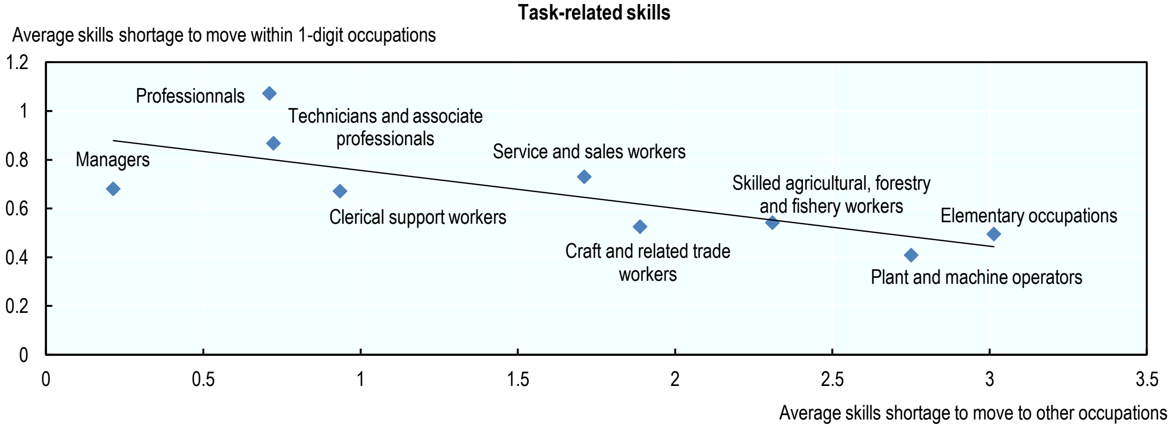
Figure 3.3. Skills shortages to move within the same ISCO-08 one-digit occupation category

Relationship between the average shortage for transitions in the same ISCO-08 one-digit occupations category and the average shortage for transitions to all other occupations

General cognitive skills



Task-related skills



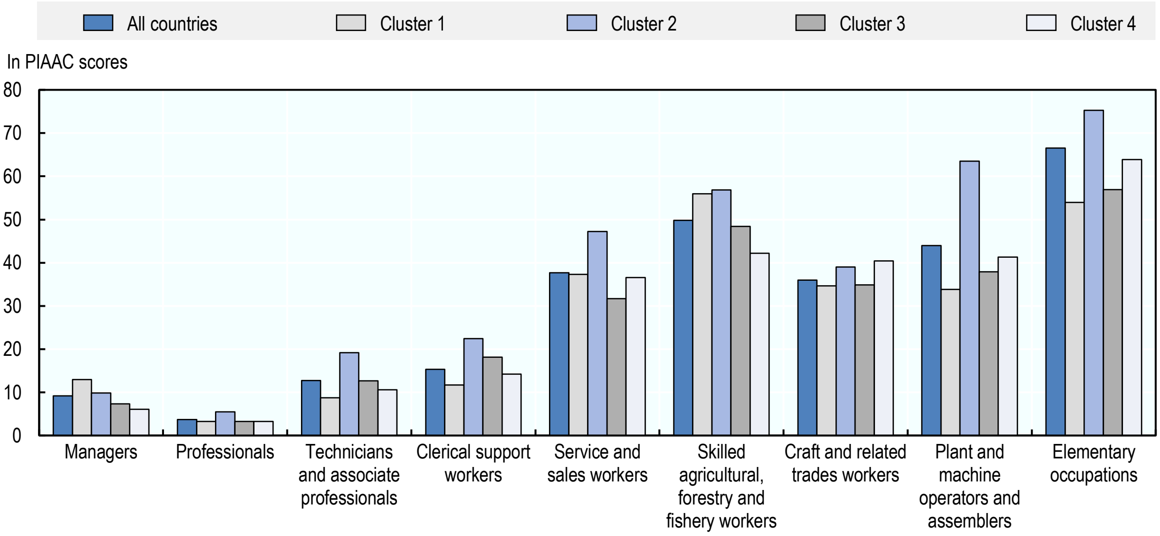
Note: Occupations refer to the three-digit codes of 2008 International Standard Classification of Occupations (ISCO-08), while occupations group refers to the one-digit ISCO-08 codes. The average shortage to all other occupations is calculated as the average of the average shortages of each occupation belonging to that occupations group to all other occupations outside this group. The average shortage to move within one-digit occupations (occupations group) is calculated as the average of average shortage for each occupation to the other occupations belonging to that occupations group.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973456

Distances between occupations vary by clusters of countries. Cluster 2, made up of Anglo-Saxon countries, stands out as having larger distances between occupations than other groups of countries, for almost all groups of occupations, reflecting more dispersed skills distributions (Figure 3.4). Cluster 1, featuring countries characterised by lower proficiency, exhibits small distances between occupations for low-skilled occupations. In Cluster 3, characterised by high skills proficiency and low skills dispersion, distances between occupations are small for most groups of occupations.

Figure 3.4. Average shortage in cognitive skills to all other occupations, by country clusters and groups of occupations



Note: Each bar shows, for each country cluster, the average shortage for occupations belonging to the indicated group of occupation (e.g. managers) to move to any other occupation. For example, occupations in the group of managers have on average much smaller shortages than occupations in the group elementary occupations to move to any other occupation. The composition of clusters is given in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973475

Where workers could move: possible and acceptable transitions

Once the distance between occupations is assessed, another question is to identify transitions between occupations that are possible to achieve within a defined upskilling or reskilling effort and are acceptable for workers, economies and societies. Those transitions need to maintain workers in quality jobs that make the best use of their skill sets. A related document explains more in detail the typology of possible and acceptable transitions and the implication for skills needs (Bechichi et al., 2019[8]).

Methodology: Defining neighbourhoods of possible and acceptable transitions

For each occupation, the analysis identifies transitions to other occupations involving (re)training or upskilling needs that could be bridged within pre-determined training effort. To this end, three training scenarios are considered:

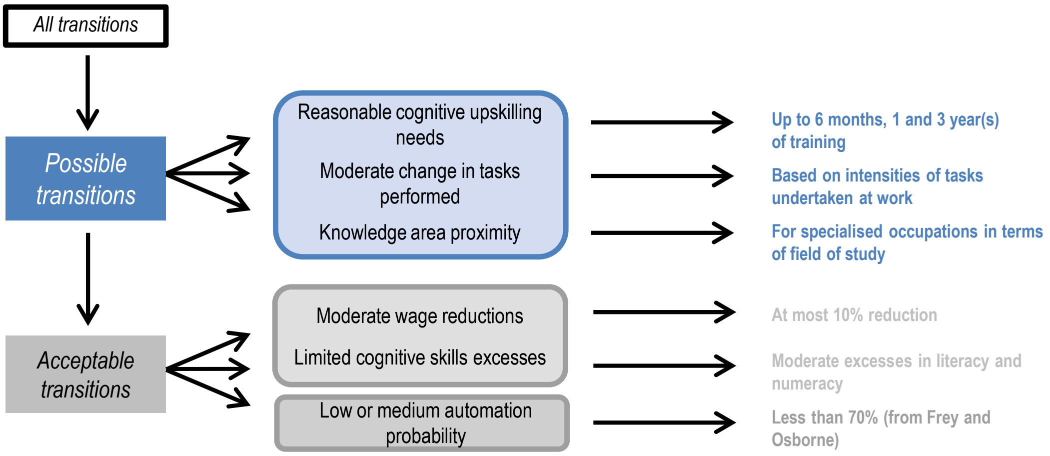
- Scenario 1 *small* training needs, which refers to (re)training or upskilling needs that can bridged within approximately six months of training at most;
- Scenario 2, *moderate* training needs, which could be bridged in approximately up to one year of training;
- Scenario 3, *important* training needs, which could be bridged in approximately up to three years of training.

In the context of any of these three scenarios, two types of transitions are distinguished: possible and acceptable transitions. Possible transitions can be made within the training effort of the scenario considered. These include transitions from high-skilled occupations to much less skilled ones. Acceptable transitions represent the subset of possible transitions that workers, and society more broadly, may be prepared to accept as they entail limited human capital and wage losses. Using a different methodology and data from the United States, a similar analysis is proposed by the World Economic Forum (2018[9]).

More specifically:

- *Possible* transitions are those for which a given upskilling or (re)training effort would close the skills distance existing between two occupations. The skills distance has two components, as explained in the previous section: cognitive skills and task-based skills. In addition, workers are unlikely to move to occupations that involve very different areas and therefore, there should be a proximity in the knowledge area of the occupation of origin and destination.
- *Acceptable* transitions are possible transitions entailing at most moderate wage reductions and limited excess cognitive skills.
- Figure 3.5 and Figure 3.6 explain the concepts used in the following sections.

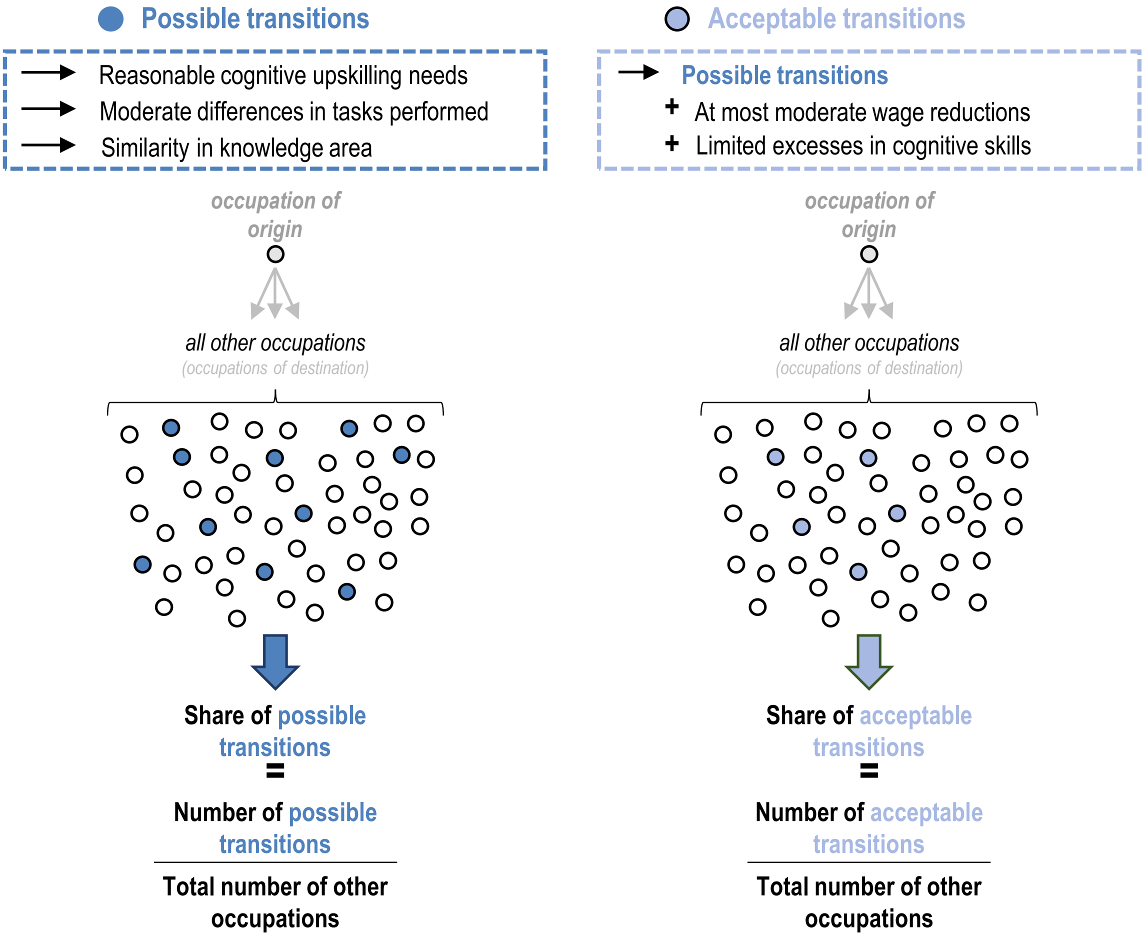
Figure 3.5. Summary of criteria for identifying possible and acceptable transitions



Policies may target acceptable transitions from occupations at high risk of automation to occupations at low or medium risk of automation. Hence, the risk of automation can be added in the analysis as a supplementary criterion guiding the identification of acceptable transitions (in final sections of this chapter). The risk of automation by occupation is taken from Frey and Osborne (2017[10]). These risks were calculated based on machine learning experts' assessment of which tasks could technically be automated and applied to the

Occupational Information Network (O*NET) data from the United States. These estimates assess the intrinsic risk of automation and therefore, are used in this analysis to identify occupations at risk of automation.

Figure 3.6. Concept used in the analysis of possible and acceptable transitions



Identifying transitions that can be made possible by a given (re)training or upskilling effort and can be acceptable is a thorny issue that is central to the analysis. It consists of assessing the extent to which cognitive skills shortages, task-based skills shortages and difference in knowledge areas can be bridged with a given training effort, or scenario. It also consists of assessing the extent to which wage reductions and skills excesses would not be acceptable, from both an individual and economy point of view. Those assumptions are detailed in Table 3.2 and discussed in a related study (Bechichi et al., 2019[8]).

Table 3.2. Summary of conditions for possible and acceptable transitions for each scenario

	Scenario 1 Small training need (up to 6 months of training)	Scenario 2 Moderate training need (up to 1 year of training)	Scenario 3 Important training need (at most 3 years of training)	Explanations
Possible transitions				
Cognitive upskilling	At most 3.5 PIAAC points in literacy and numeracy	At most 7 PIAAC points in literacy and numeracy	At most 21 PIAAC points in literacy and numeracy	The equivalence between years of education and cognitive skills is obtained from regressing PIAAC cognitive skill scores on years of education controlling for a number of factors.
Task up- or reskilling	At most bottom quartile	At most median	At most top quartile	These values correspond respectively to the bottom quartile, median, and top quartile of the distribution of task-based skills shortages (excluding zeros).
Knowledge area proximity	*If specialised destination occupation*: one of the most frequent fields of study of the occupation of origin needs to be among the most frequent fields of study of the specialised occupation of destination *Otherwise*: no restriction		No criteria applied	An occupation's set of most frequent fields of study corresponds to the most common fields of study which together account for at least 50% of the occupation's workers. An occupation is defined as specialised if the workers composing this occupation are concentrated in only a few fields of study.
Acceptable transitions				
Moderate wage reductions	At most 10%			This figure corresponds to approximately the average annual earnings loss one year after displacement in five OECD countries, (OECD, 2013[11]).
Limited cognitive skills excesses	3.5 PIAAC points	7 PIAAC points	7 PIAAC points	For Scenario 1 and Scenario 2, this condition mirrors the maximum allowed cognitive skills upskilling needs. For Scenario 3, the same condition as Scenario 2 is chosen to avoid a large human capital loss.

Source: Bechichi, N. et al. (2019[8]), "Occupational mobility, skills and training needs", OECD, Paris.

In particular, the approach rests on estimates of the cognitive skill shortages that can be bridged within one year of education. Due to data limitations, it is not possible to causally estimate skills returns to education using PIAAC data but only to rely on correlations between cognitive skills and educational level, which account for a number of factors (Bechichi et al., 2019[8]). This approach finds that one year of education makes up for approximately 7 PIAAC literacy and 7 PIAAC numeracy points.

Several caveats surround the choice of the equivalence between years of education and cognitive skills, which is a crucial parameter for the analysis:

- The skills returns to education vary between countries, because some have better education systems than others or because framework conditions differ. As the estimated equivalence is taken over all countries, it represents an average of all the countries included in the analysis and is therefore sensitive to, for example, the inclusion or exclusion of some countries. The main implication of this choice is that, for a given training effort, the transition options may be underestimated for countries with high-performing education and training systems, and overestimated for those with low-performing systems or with large heterogeneity of educational institutions.

- The analysis further assumes that each individual learns at equal pace once in training. Workers are likely to have different learning abilities, however, depending factors such as the type of education they went through as students, their attitude to learning, their skills and knowledge, and their age. The analysis also assumes that individuals complete the education and training programme and that this programme is successful in upskilling.
- Expressing a training effort in terms of duration is questionable in itself as several factors beyond duration affect what participants will actually learn, including resource endowment, curricula and pedagogical approaches. However, the use of an equivalence between cognitive skills shortages and years of education makes it possible to measure training efforts and estimate the cost of training for governments and countries.
- While these estimates cover the training effort required to bridge cognitive skills needs, they cover task-based skills needs only partly. The equivalence between cognitive skills shortages and years of education cannot be reproduced for skills. Task-based skills are more likely to be developed on the job and there is no data on how much an hour of (e.g. vocational) training yields in terms of task-based skills' gain. However, some of the tasks-based skills considered in this study are also partially cognitive, such as ICT, advanced numeracy, and management and communication skills. Hence, it is likely that improving workers' cognitive skills also enhances some of their task-based skills, but the present methodology cannot say how much so. For these reasons, the training effort required to move between occupations may be underestimated.
- Because of the lack of data on non-formal training, estimates build on the skills returns to formal education. The analysis assumes that the training provided to workers, often non-formal training, would lead to the same cognitive upskilling as formal education. This assumption does *not* imply that training needs to be provided by the formal education sector. Years of education data are used as a reference, in the absence of more complete information about training duration and outcomes (and cost for the next sections).

For all these reasons, references to scenarios in terms of duration of training should be considered as tentative and indicative of how small, moderate or important training needs can be.

The analysis identifies neighbourhoods of occupations that can be reached for a given occupation of origin by a given increase in skills. While education and training policies can lead to such skills development, workers can also learn by themselves, from co-workers and by doing. Box 3.3 discusses other caveats related to the analysis presented in this chapter.

Box 3.3. Methodological caveats

This chapter presents estimates of the training needs and costs of education and training policies to facilitate occupational mobility. To identify a typology of occupational transitions and to generate cost estimates for a large number of countries given the data limitations encountered, several simplifying assumptions are made that inevitably influence the results. These aspects are discussed in background studies (Andrieu et al., 2019[12]; Bechichi et al., 2019[8]) and summarised below. Implications for estimates are explained in detail in Annex Table 3.A.1.

Choice of parameters for identifying possible and acceptable transitions

The definition of possible and acceptable transitions relies on a limited number of parameters that workers are likely to consider when changing jobs. Currently these include cognitive and task-based skill excesses or shortages, and differences in wages and field of education specialisation between occupations of origin and destination. However, preferences over the maximum acceptable wage cut or human capital loss that individuals are willing to accept to re-enter employment depend on individuals, countries and the type of transition, either voluntary or involuntary. In addition, preferences about location, contract type, or differences in a worker's match with the position (Groes, Kircher and Manovskii, 2015[13]), to name but a few important ones, are not considered. In this sense, this analysis identifies feasible opportunities for occupational mobility, but cannot predict it.

Lack of worker heterogeneity

The analysis further assumes that workers learn at an equal pace and can acquire at most 7 PIAAC points in both literacy and numeracy in a given year of education. Workers, however, are likely to have different learning abilities. Furthermore, the quality of education and the efficiency of the education sector can differ widely across locations and countries, yielding different training time for different individuals. Relaxing these assumptions, however, requires considering a high level of disaggregation in the PIAAC data and a large quantity of recent data on education systems across countries, which is unfeasible in the context of the present study. Furthermore, "individual proficiency in learning" and the "efficiency" of an education or training system are hard to measure, especially in a uniform way across countries.

Lack of consideration of transitions *within* the same occupation

The analysis only considers the cost of moving from one occupation to another, with a special focus on moving away from occupations at high risk of automation. In reality, transitions within occupations do exist and can entail a cognitive retraining effort, because skill requirements vary between employers a worker's skill set has depreciated or the skill content of an occupation has changed. These transitions may be less costly than those presented in the analysis if the skills distance between jobs belonging to the same occupation is smaller than the skills distance between two different occupations. However, transitions within occupations may not help workers move away from the risk of automation to the same extent as the transitions between occupations considered in the analysis.

Uncertainty surrounding estimates of automatability

The analysis distinguishes between occupations at high versus medium or low risk of automation, while the risk of automation is a continuum that affects all occupations. Furthermore, workers may differ in their risk of displacement due to automation even within the same occupations, depending on the type of technology deployed, the organisation of tasks in their job place, their sector of affiliation or other institutional settings. The analysis cannot account for changes over time in the skill content of occupations, as it relies on cross-sectional data varying between occupations and countries but not over time. This may entail an overestimation of the cost figures presented if occupations at high risk of automation evolve towards a lower risk of automation, or an underestimation if low-risk occupations are quickly automated.

Exclusion of sectoral dimension

The proposed analysis does not consider whether job transitions imply changing the sector of employment. This was mostly driven by data constraints. While much of the economic literature on labour mobility corroborates this assumption (Kambourov and Manovskii, 2009[14]), others disagree and provide evidence of the coexistence of sectoral and occupational switching costs (Sullivan, 2010[15]) or simply of sector-specific costs (Dix-Carneiro, 2014[16]).

Workers transition directly to a different occupation, without going through an unemployment spell

Workers that switch occupations are assumed to move from the original job to education or retraining and then to the new job without discontinuity or unemployment spells. Such frictionless transitions are likely to be unrealistic for most workers, especially for those who are made redundant and did not leave their job voluntarily. Periods of unemployment may depreciate workers' skills and therefore widen the skill gap, which needs to be bridged for workers to re-enter employment. Idle times during transitions increase the opportunity cost of staying out of employment, while longer training times increase the direct cost of transitions.

Lack of general equilibrium or dynamic elements

Lastly, no general equilibrium or dynamic elements are incorporated in this analysis. In other words, no issues are considered that relate to the adequacy between the number of workers needing training (labour supply) and the number of job openings in "safe haven" occupations (labour demand), which in turn affects the relative wages of occupations. Moreover, the analysis does not include in the indirect cost the fact that some workers may move to higher-paying occupations, which influences their future wage profile, to clearly separate the elements that pertain to costs and those pertaining to gains.

Sources: Andrieu, E. et al. (2019[12]), "Occupational transitions: The cost of moving to a "safe haven"", https://doi.org/10.1787/6d3f9bff-en ; Bechichi, N. et al. (2019[8]), "Occupational mobility, skills and training needs", OECD, Paris; Groes, F., P. Kircher and I. Manovskii (2015[13]), "The U-Shapes of occupational mobility", http://dx.doi.org/10.1093/restud/rdu037; Kambourov, G. and I. Manovskii (2009[14]), "Occupational mobility and wage inequality", http://dx.doi.org/10.1111/j.1467-937X.2009.00535.x; Sullivan, P. (2010[15]), "Empirical evidence on occupation and industry specific human capital", http://dx.doi.org/10.1016/J.LABECO.2009.11.003; Dix-Carneiro, R. (2014[16]), "Trade liberalization and labor market dynamics", http://dx.doi.org/10.3982/ECTA10457.

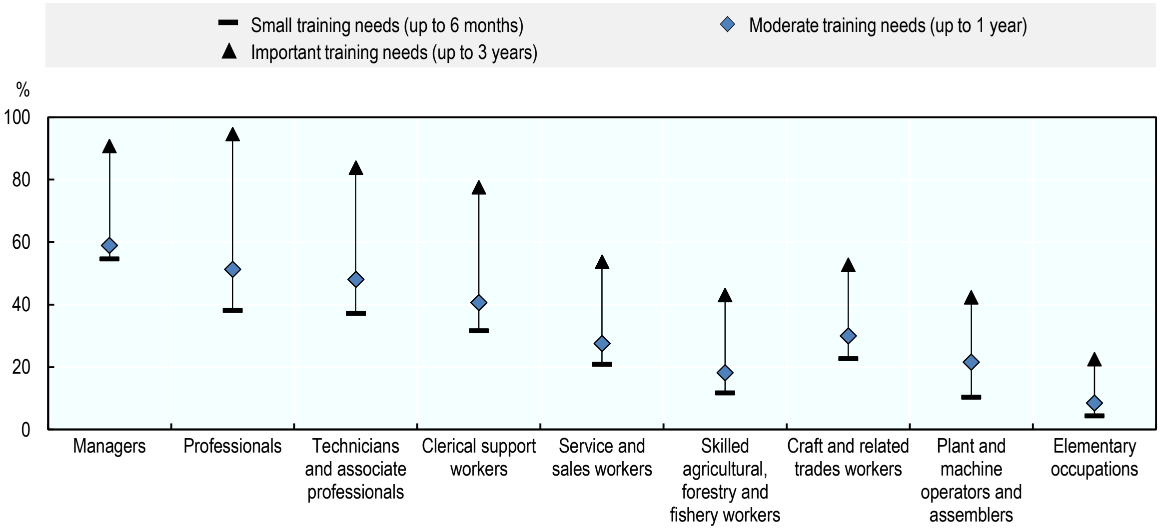
Results: Which transitions for any worker?

In a first step, all occupations and all transitions are considered, without taking into account the risk of automation associated to an occupation.

Most occupations appear to be fairly close to some other occupations in terms of cognitive skills requirements, task content, and knowledge area. This is reflected in the fact that for almost all occupations, it is possible to identify possible transitions in Scenario 1 involving small retraining needs (Figure 3.7). On average, more skilled occupations face several possible transitions in all scenarios, as there are many options to move, even to less skilled occupations. This is true for all three scenarios. For example, within six months of (re)training, managers could move to almost 60% of occupations, whereas workers in elementary occupations could switch to only 5% of all possible occupations, given their skills' endowments and needs. Clerks also have many possible transitions, thanks to their high cognitive skills and the variety and frequency of the tasks they perform on the job (or task-based skills).

Figure 3.7. Average share of possible transitions by group of occupations and scenario

As a share of the total number of occupations, all countries



Note: Each dot shows, for each group of occupations, the average share of possible transitions out of the total number of occupations in the sample, by scenario. For example, in the small training needs scenario, managers, on average, have 55% of possible transitions. In other words, for the average manager occupation, 55% of transitions to all other occupations could technically be bridged within approximately six months. Table 3.2 summarises the conditions used to identify possible transitions.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973494

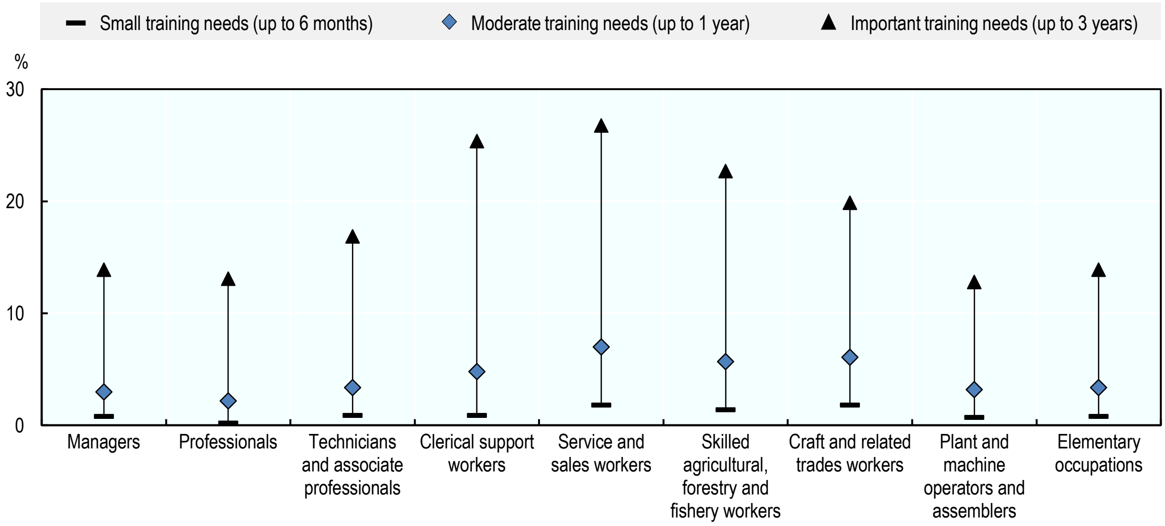
If transitions are required to involve limited cognitive skills excesses and wage reduction, many possible transitions can no longer be considered acceptable, especially for high-skilled occupations (Figure 3.8). For example, within six months of (re)training, less than 1% of the transitions of managers to other occupations could be considered as acceptable.

As the upskilling or (re)training effort increases, it is possible to identify a larger number of acceptable transitions: the share of acceptable transitions increases from Scenario 1 to 3. This is because allowing more (re)training time increases the share of possible transitions. In addition, as it is assumed that workers undertaking longer training spells may transit to occupations that are slightly less cognitively demanding but perhaps involve different task-based skills, the pool of acceptable transitions increases with the retraining effort. With a large training effort of up to three years, some occupations can move to any other occupation, and therefore have 100% of acceptable transitions. This is because the pool of possible transitions is further increased and the condition on the knowledge area is relaxed in Scenario 3.

The relationship between the number of acceptable transitions enabled by upskilling or (re)training efforts and the skill level of occupations is bell-shaped. This finding holds when considering occupation categories as an indication of the skill level (Figure 3.8) or considering directly the average literacy skills of workers of three-digit ISCO-08 occupations (Figure 3.9). There are few acceptable transitions from low-skilled occupations to other occupations because other occupations involve more demanding skills requirements; there are not many acceptable transitions from high-skilled occupations to other occupations because several transitions would entail big wage decreases or skills excesses.

Figure 3.8. Average share of acceptable transitions by groups of occupations and scenarios

As a share of the total number of occupations, all countries



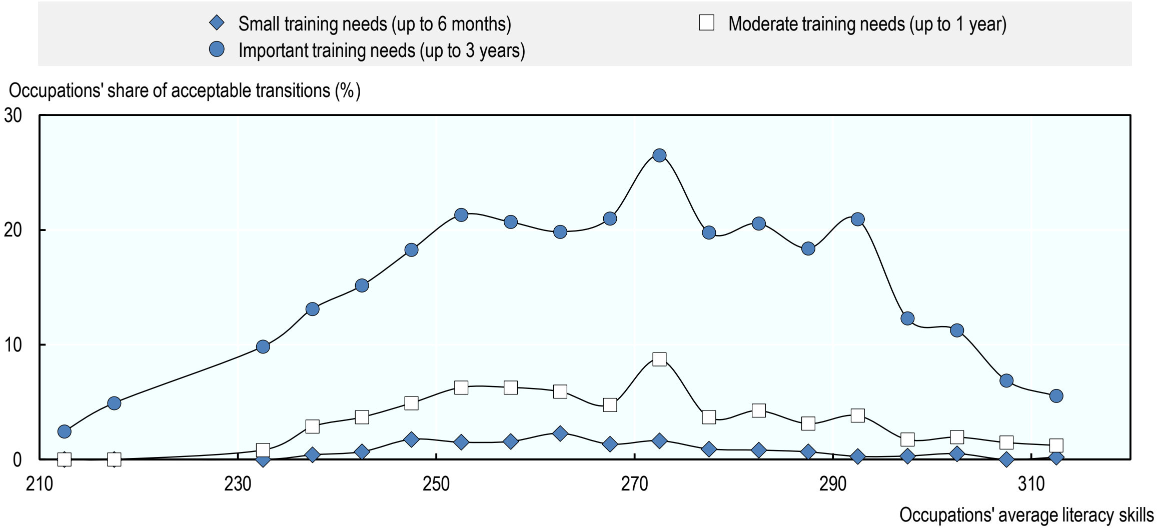
Note: Each dot shows, for each group of occupations, the average share of acceptable transitions out of the total number of occupations in the sample, by scenario. For example, in the small training needs scenario, managers, on average, have less than 1% of acceptable transitions. In other words, for the average manager occupation, less than 1% of transitions to all other occupations could technically be bridged within approximately six months while entailing skills excesses and wage decrease below the limit set for this scenario. Table 3.2 summarises the conditions used to identify acceptable transitions.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973513

Figure 3.9. Average share of acceptable transitions by literacy skills and scenarios

As a share of the total number of occupations, all countries



Note: This figure displays occupations' share of acceptable transitions as a function of their average literacy skill score, for each scenario. To facilitate readability, literacy scores are grouped in 5-point bins and acceptable transition shares are averaged by 5-point bin. For example, occupations whose average literacy score falls between 270 and 275 points (just to the right of the 270 tick) have an average share of acceptable transitions of 1.6 in the small training needs scenario and 8.7 in the moderate training needs case. Table 3.2 summarises the conditions used to identify acceptable transitions.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

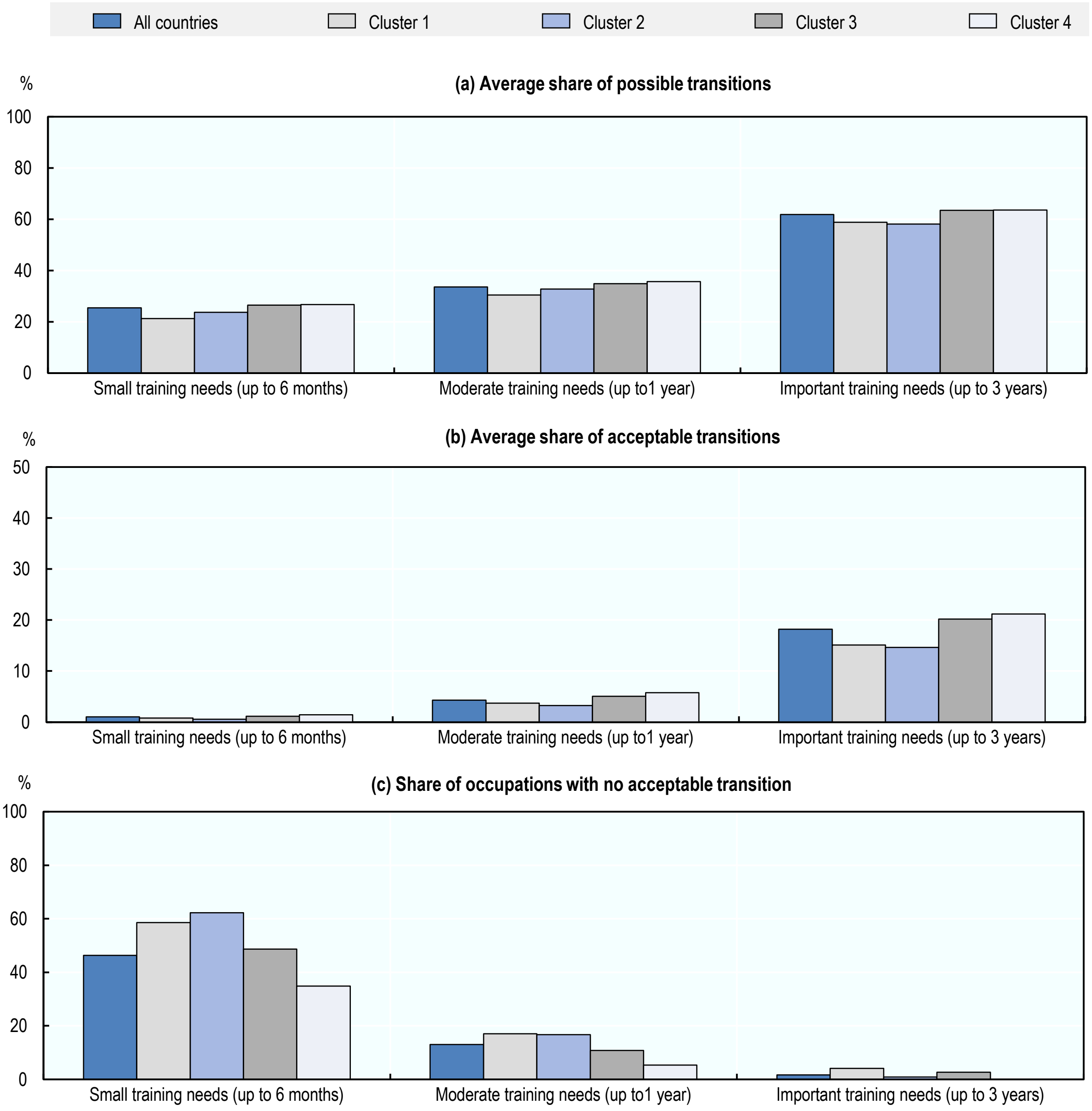
StatLink https://doi.org/10.1787/888933973532

Country specificities of occupational transitions

Opportunities for workers to change occupation depend on several country specificities, including geographical location of economic activity, industry structure and dynamics, institutional barriers (such as occupational licensing), flexibility of labour market arrangements, and skills' distribution. In countries where the distribution of workers' skills is highly uneven, occupations tend to be farther away from one another – and mobility between occupations more difficult – than in countries with narrow skill distributions.

Differences between countries in the distances between occupations affect the numbers of possible and acceptable transitions (Figure 3.10). In countries with larger distances between occupations (clusters 1 and 2), fewer possible transitions can be identified and, consequently, there are also fewer acceptable transitions. In these countries, some possible transitions would entail large skills excesses and wages are more unevenly distributed, so a bigger share of possible transitions involves wage decreases. For clusters 3 and 4, a bigger share of possible and acceptable transitions can conversely be identified. The number of occupations for which no acceptable transitions can be identified with a given training effort also varies by cluster. This is more often the case in clusters 1 and 2 than in clusters 3 and 4.

Figure 3.10. Average share of possible and acceptable transitions, by country cluster



Notes: Panel (a) shows the average share of possible transitions by country cluster and training duration. For example, in the small training needs (up to six months) scenario, for cluster 1, occupations have an average of 21% of possible transitions (out of all transitions), and 30% in the moderate training needs case. Panel (b) shows the average share of acceptable transitions by country cluster and training duration. For example, in the important training needs (up to three years) scenario, for cluster 2, occupations have an average of 15% of acceptable transitions. Panel (c) shows the share of occupations that have no acceptable transition by country cluster and training duration. For example, taking all countries together, there are about 45% of occupations that do not have an acceptable transition in the small training needs case, while this share decreases to 13% in the moderate case.

Possible and acceptable transitions are defined in Table 3.2. Clusters are defined in Table 3.1.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973551

Which transitions to move away from the risk of automation

While the number of occupations that can be fully automated may not be large, at least in the short-run, education and training policies can aim to facilitate transitions from occupations at high risk of automation to those at a lower risk.

In the following sections, the risk of automation is added to the analysis as a supplementary criterion guiding the identification of acceptable transitions (Box 3.4). The analysis builds on available estimates but large uncertainties need to be acknowledged concerning the number of occupations that would be less in demand in the future and the share of workers who might need to change occupations (Box 3.3).

The analysis identifies "safe havens" or occupations of destination involving a transition with minimum upskilling or (re)training efforts, moderate wage reductions, limited skills excesses and a low or medium risk of automation.

The minimum training effort required to move to a "safe haven" for occupations at high risk of automation is calculated as the average training time in: Scenario 1 if *small* training efforts lead to a "safe haven", Scenario 2 if *small* training efforts do not lead to a "safe haven" but *moderate* training efforts do, Scenario 3 if important training efforts are necessary to move to a "safe haven" (Figure 3.11).

Box 3.4. Estimating occupations' risk of automation

Frey and Osborne's methodology

Frey and Osborne (2017[10]) estimated how potential technological improvements might affect future employment in the United States, with the aim of quantifying the "susceptibility of jobs to computerisation". They focused on the theoretical possibility of automating a task or job rather than on the actual automation of tasks or jobs, and proceeded as follows:

1. During a workshop at Oxford University, they asked a group of machine learning researchers to assess the automatability of 70 occupations based on their O*NET task description. The exact question was "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer-controlled equipment?" Occupations for which all tasks were confidently considered to be automatable were assigned a 1, while occupations for which none of the tasks were confidently considered to be automatable were assigned a 0.
2. Based on the answers for the 70 occupations of the workshop, they used a machine learning algorithm to better understand the link between their automatability and three "bottlenecks to computerisation" (perception and manipulation; creative intelligence; and social intelligence). The results from the algorithm enabled them to estimate the probability of computerisation for 702 detailed occupations for which employment and wage data are reported by the Bureau of Labor Statistics (BLS).

Automation risk categories

Frey and Osborne (2017[10]) classify occupations into three broad categories, which are also followed in the present work:

- *Low risk of automation*: 30% or less probability of computerisation;
- *Medium risk of automation*: between 30% and 70% probability of computerisation;
- *High risk of automation*: over 70% probability of computerisation.

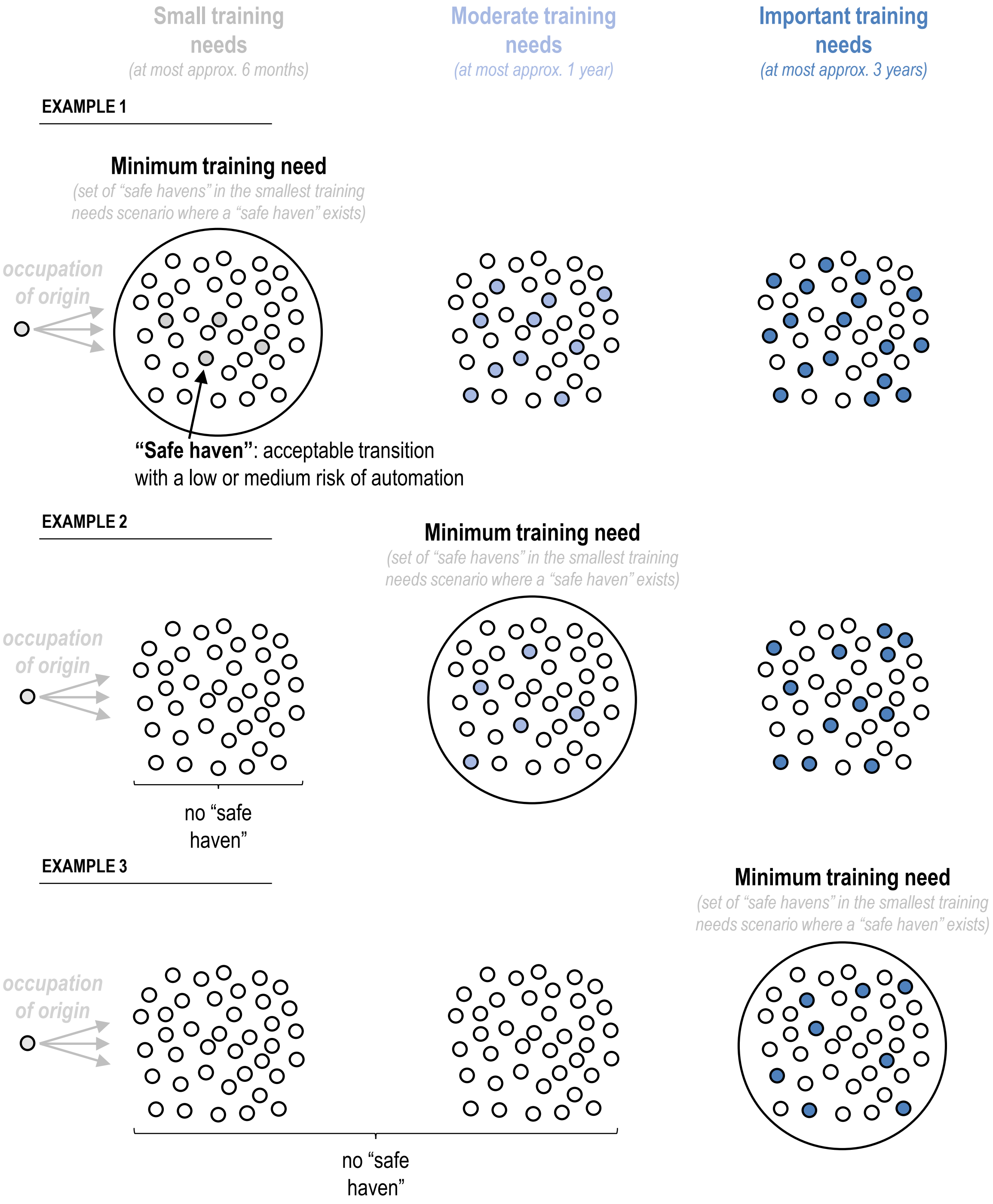
Share of employment at high risk in occupations at high risk of automation

Deriving the share of employment in jobs at high risk of automation requires making an assumption about whether all workers in the same occupation face the same risk or not. Workers in the same occupation may perform different tasks, depending on the organisation of the firm, for example, and the industry in which work, and may therefore face different risks of their job being automated (Arntz, Gregory and Zierahn, 2016[17]; Nedelkoska and Quintini, 2018[18]). Therefore, in the following sections, two cases are considered:

1. Only a proportion of workers in a given occupation at high risk of automation are in jobs at high risk of automation. This assumption leads to lower bound estimates in the following sections, ranging from 4% to 10% of employment depending on the country. The proportions of workers in jobs at high risk of automation for all high risk of automation occupations come from Nedelkoska and Quintini (2018[18]);
2. All workers currently employed in a given occupation at high risk of automation are in jobs at high risk of automation. This assumption leads to upper bound estimates in the following sections, ranging from 19% to 48% of employment depending on the country.

Sources: Frey, C. and M. Osborne (2017[10]), "The future of employment: How susceptible are jobs to computerisation?", http://dx.doi.org/10.1016/J.TECHFORE.2016.08.019; Arntz, M., T. Gregory and U. Zierahn (2016[17]), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", http://dx.doi.org/10.1787/5jlz9h56dvq7-en; Nedelkoska, L. and G. Quintini (2018[18]), "Automation, skills use and training", https://dx.doi.org/10.1787/2e2f4eea-en..

Figure 3.11. Minimum training needed to find a "safe haven": Definition



Note: In Example 1, an acceptable transition to an occupation with a low or medium risk of automation is identified in the scenario as involving approximately six months of training, hence the minimum training needed to find a "safe haven" is small (around six months). The minimum training needed to reach a "safe haven" is moderate in Example 2 as no "safe haven" can be reached with a small training effort and important in Example 3 as no "safe haven" can be reached with a small or moderate training effort.

Occupations at high risk of automation requiring important investment in training

Occupations at high risk of automation display, on average, shares of possible and acceptable transitions similar to those of occupations at low risk of automation, i.e. the two groups of occupations of origin have similar potential for mobility (Bechichi et al., 2019[8]). When the set of acceptable occupations *of destination* is constrained to occupations displaying low or medium risk of automation (less than 70%) – "safe haven" occupations – this restricts further the set of acceptable transitions.

The (re)training or upskilling efforts necessary to identify acceptable transitions from occupations at high risk of automation to low- or medium-automation-risk occupations varies by country cluster (Figure 3.12). When all countries are considered together, within up to six months of (re)training (i.e. Scenario 1), about half of the occupations at high risk of automation do not have any acceptable transition to an occupation at lower risk of automation. This share climbs to close to 80% for clusters 1 and 2, and just over 65% for cluster 3. Results for cluster 4 are similar to those obtained for all countries. These shares are halved or more when extending the duration of (re)training to up to one year (Scenario 2). With a large training effort (Scenario 3), acceptable transitions to occupations at smaller risk of automation can be found for all occupations in clusters 2 and 4, and for most of them in clusters 1 and 3.

Differences between clusters partly reflect those observed for acceptable transitions in general. For countries with a dispersed cognitive skills distribution (clusters 1 and 2), it is difficult to find transitions when small (re)training efforts are considered, and even more so when restricting transitions to those occupations at low or medium risk of automation.

These findings highlight the role of the skills distribution for occupational mobility and the implications for education and training policies. When workers' skills are dispersed, occupations tend to be more distant from one another in their skills requirements and the training effort required to switch occupations is larger. Designing effective options to learn on the job is crucial in these countries. In countries with a small skills dispersion but a low level of skills, workers may find options to move to other occupations with a small retraining effort in the short term, but in the long term the development and adoption of new technologies needed to maintain or increase countries' competitiveness and growth would require larger investment in education and training.

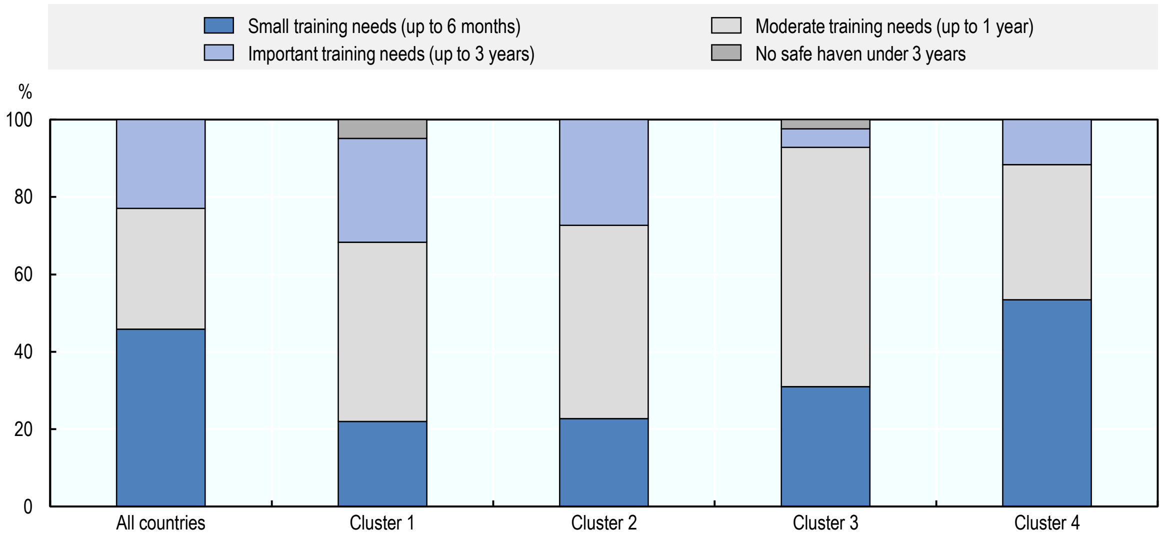
The analysis enables the identification of occupations at risk that education and training policies may need to focus on: those at high risk of automation for which a training effort of more than one year is required to move to occupations at low or medium risk of automation (Table 3.3). Occupations at high risk of automation can be considered as being less at risk if it is possible to identify acceptable transitions to occupations at lower risk of automation with a small or moderate training effort (six months to one year).

The share of employment in occupations at high risk of automation for which an important training effort is required to move to occupations at low or medium risk of automation varies across countries. This share also depends on whether it is assumed that all workers in those occupations are at high risk (upper bound) or that only some of them are at high risk (lower bound) (Arntz, Gregory and Zierahn, 2016[17]; Nedelkoska and Quintini, 2018[18]).

Overall, the share of employment that may be of specific concern for policies ranges between 0.4% and 1.5% for the lower bound and between 2% and 6% for the upper bound (Figure 3.13).

Figure 3.12. Share of occupations at high risk of automation with at least one acceptable transition to occupations at low or medium risk of automation by smallest training need for which such a transition can be found

For all countries and by cluster, as a share of occupations at high risk of automation



Notes: For each country cluster, this figure displays the share of occupations at high risk by the training needs to find its closest acceptable transition with a low or medium risk of automation. For example, when all countries are considered together in the analysis, 45% of the occupations at high risk of automation need a small training effort to find an acceptable transition to an occupation with a low or medium risk of automation, around 30% need a moderate training effort to find such a transition, and the remaining 25% require an important training effort. The risk of automation of origin occupations is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4. Occupations with a low risk of automation have an automation probability below 30%, medium automation risk between 30% and 70%, and high automation risk over 70%. Acceptable transitions are defined in Table 3.2. Clusters are defined in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Table 3.3. Occupations that may need to be targeted by training programmes

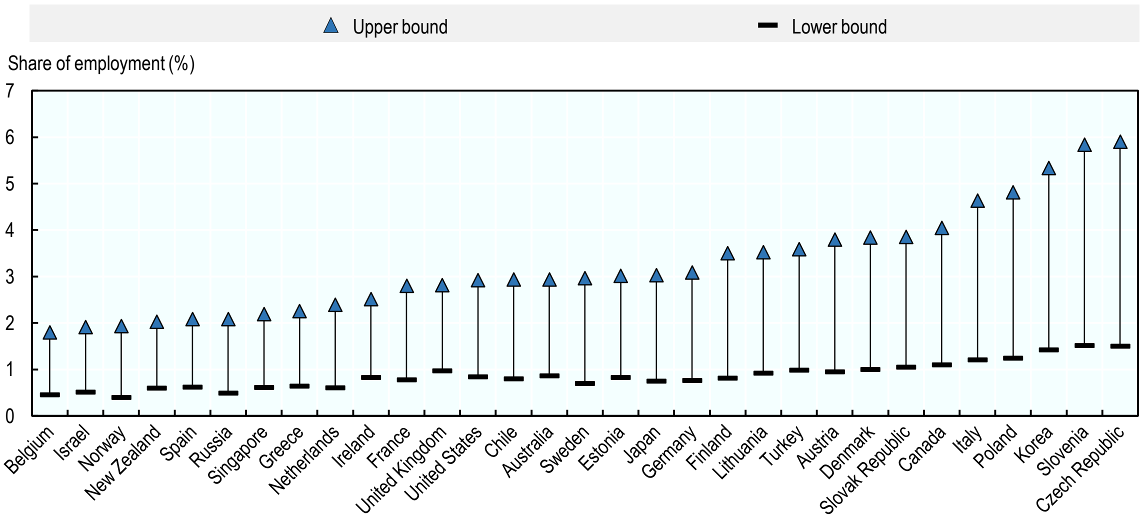
Occupations at high risk of automation not having any acceptable transition to occupations at low or medium risk of automation with training of up to one year

Occupations	Risk of automation
Blacksmiths, toolmakers and related trades workers	84.8
Chemical and photographic products plant and machine operators	85.0
Keyboard operators	96.6
Medical and pharmaceutical technicians	78.8
Metal processing and finishing plant operators	88.0
Mining and construction labourers	80.0

Occupations	Risk of automation
Mining and mineral processing plant operators	80.4
Rubber, plastic and paper products machine operators	86.7
Street vendors (excluding food)	94.0
Subsistence livestock farmers	87.0
Wood processing and papermaking plant operators	82.1

Note: These occupations are occupations at high risk of automation and without any acceptable transition to occupations at low or medium risk of automation, when training spells of up to one year are considered (Scenario 2). The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4. Low automation risk occupations correspond to occupations with an automation probability below 30%; medium automation risk: between 30% and 70%; high automation risk: over 70%. Acceptable transitions are defined in Table 3.2. Calculations are based on results when countries are considered together.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

Figure 3.13. Share of employment in occupations at high risk of automation for which an important training effort is needed to transition to occupations at low or medium risk of automation



Note: For the lower bound estimate, only workers in jobs currently at high risk of automation are considered while for the upper bound estimate, all workers currently employed in occupations at high risk of automation are considered. The proportion of workers in jobs at high risk of automation in an occupation is taken from Nedelkoska and Quintini (2018[9]). The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]). Those aspects are described in Box 3.4.
Sources: Authors' own calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973589

Assessing the cost of education and training needed to move away from the risk of automation

The final question is to estimate the costs of the training efforts required, in each of the 31 OECD member countries in the analysis, to help workers in occupations at high risk of automation move to "safe havens". A related document explains how to assess the cost of the education and training needed to help workers switch occupations (Andrieu et al., 2019[12]).

Methodology: Defining total, direct and indirect training costs

For each occupation at high risk of automation in each country, the analysis calculates the monetary cost of transitions for an average worker from these occupations of origin to an average "safe haven".

The minimum cost is the cost corresponding to the minimum training effort/need.

Occupations' per-worker total cost of training in a country is equal to the sum of two types of costs:

- *Direct cost:* the actual cost of providing training to a worker to move to a given "safe haven" for the length of the considered training spell. An occupation's direct cost is equal to the training time required to move to a "safe haven" multiplied by the education and training cost per year (proxied by the country's per-pupil annual education expenditure), averaged over all of the occupation's "safe havens" given a certain training effort.
- *Indirect cost:* the opportunity cost of training, corresponding to the wages foregone by a worker during the training spell, assuming that workers do not work during training. An occupation's indirect cost is equal to the training time required to transition to a "safe haven" multiplied by the occupation's median annual wage, averaged over all of the occupation's "safe havens" given a certain training effort.

Once direct and indirect costs have been computed for each occupation in each country, the country-level direct and indirect costs are obtained by summing over all occupations' direct and indirect costs, multiplying by occupations' number of workers in the country. The methodology is explained in Box 3.4.

To compute these estimates several simplifying assumptions were made. First, the cost of training was assumed to be the same for all workers in the same occupation in the same country. In other words, no hypothesis is made regarding how a worker's characteristics, such as their skill or education level, their age, their geographical location or their professional experience, would affect their training cost.

Second, due to the lack of reliable data on countries' expenditures on training, countries' education expenditures are used as a proxy. This assumes that workers retrain through formal or non-formal education and training programmes, but not through learning at work or at home with open educational resources, or though informal learning (e.g. learning from co-workers). Additionally, this assumes that the cost of non-formal training (e.g. on-the-job training) is the same as that of formal training in an education institution (e.g. a vocational education and training programme leading to a degree). Other methodological caveats are discussed in Box 3.3.

In sum, the total cost per occupation and country varies with: (1) the length of the training spell considered; (2) the occupational composition of the cluster; (3) the direct cost of training, which is country-specific; and (4) the wages underlying the indirect cost, which are cluster-specific.

Box 3.5. Computing countries' costs of occupational mobility

Total cost decomposition

The total cost for an average worker to move from occupation o in country i to another occupation is decomposed into two elements, the direct and indirect cost:

$$Total\ Cost_{i,o} = Direct\ Cost_{i,o} + Indirect\ Cost_{c_i,o},$$

where $TotalCost_{i,o}$ is the total training cost of occupation o in country i, $DirectCost_{i,o}$ is the direct cost of occupation o in country i, and $IndirectCost_{c_i,o}$ is the indirect training cost of occupation o in country i's cluster c_i.

Step 1: Computing direct and indirect cost at the occupation-country level

To compute training costs at the country level, it is first necessary to calculate the direct and indirect costs for every occupation in every country.

Direct cost

The direct cost of an acceptable transition from occupation o in country i to occupation d is equal to the training time required to transition to occupation d times education and training cost per year:

$$Direct\ Cost_{i,o,d} = \left(training\ time_{c_i,o,d}\right) \times (per - pupil\ education\ cost_i),$$

where $training\ time_{c_i,o,d}$ corresponds to the training time in years needed for an acceptable transition from occupation o in country i's cluster c_i to occupation d given a certain training effort, and $per - pupil\ education\ cost_i$ is country i's yearly per-student primary to secondary or tertiary cost in USD (expressed in purchasing power parities, or PPP) in 2014 as reported in the Education at a Glance (2017[19]) dataset.

Education expenditure covers the "core services", i.e. total education spending net of research and development (R&D) and ancillary service expenditure, for both private and public education institutions.[3] Thus, it does not correspond only to tuition fees paid by students. If either the occupation of origin or of destination has a majority of tertiary-educated workers, the cost of tertiary education is used. Otherwise, the cost of primary to secondary education is used. This corresponds to assuming that a worker having attained a tertiary degree does not retrain at the secondary level, while the reverse is possible. The analysis does not take into account the possibility that countries with high education expenditure per student achieve better education and training outcomes.

The direct cost of moving away from occupation o in country i is obtained by averaging direct costs over all occupation o's acceptable transitions given a certain training effort.

Indirect cost

The indirect training cost of an acceptable transition from occupation o in country i's cluster c_i to occupation d is equal to the training time required to transition to occupation d times the occupation's median annual wage:

$$Indirect\ Cost_{c_i,o,d} = \ training\ time_{c_i,o,d} \times \left(wages_{c_i,o}\right),$$

where $training\ time_{c_i,o,d}$ is defined in the same way as above, and $wages_{c_i,o}$ is occupation o in country i's cluster c_i's median annual wage expressed in USD PPP.

Again, the indirect cost of moving away from occupation o in country i's cluster c_i is obtained by averaging indirect costs over all occupation o's acceptable transitions given a certain training effort. While the direct cost for a given occupation varies across countries, the indirect cost for a given occupation varies across clusters but not across countries belonging to the same cluster.

Step 2: Aggregate direct and indirect costs at the country level

Once the (average) direct and indirect costs are computed at the occupation-country level, these can be aggregated at the country level. In particular, country i's direct and indirect cost is a weighted sum of occupations' direct and indirect costs:

$$Direct\ Cost_i = \sum_{o=1}^{O_{c_i}} emp_{i,o} \times Direct\ Cost_{i,o},$$

$$Indirect\ Cost_i = \sum_{o=1}^{O_{c_i}} emp_{i,o} \times Indirect\ Cost_{c_i,o},$$

where O_{c_i} is the total number of occupations in country i's cluster c_i, and $emp_{i,o}$ is the number of workers employed in occupation o in country i calculated from the Survey of Adult Skills (PIAAC).

Finally, country i's total training cost given a certain training effort is:

$$Total\ Cost_i = Direct\ Cost_i + Indirect\ Cost_i.$$

The cost of moving to a "safe haven"

The minimum cost of training per worker (associated to the minimum training need, Figure 3.11) required to move away from an occupation at high risk of automation is larger if the move has to be to occupations at low or medium of risk of automation than if all acceptable transitions are considered (Table 3.4). This is because acceptable occupations at low risk of automation are on average characterised by higher cognitive skill requirements.

The average minimum cost of training per worker to move away from the risk of automation varies across clusters of countries. It is higher in countries in cluster 2 (English-speaking countries) because per-student total education expenditure tends to be higher in these countries, leading to a high direct cost, and wages are also higher, leading to high indirect cost.

Table 3.4. Average minimum training costs for a worker in an occupation at high risk of automation

In ’000 USD (PPP), by type of occupations of destination

	All destinations			Only low or medium risk of automation destinations		
	Indirect	Direct	Total	Indirect	Direct	Total
Cluster 1	8.0	2.8	10.8	12.5	4.5	17.0
	(0.7)	(0.2)	(0.9)	(0.9)	(0.3)	(1.1)
Cluster 2	15.8	5.4	21.2	21.1	7.4	28.6
	(1.8)	(0.5)	(2.3)	(2.0)	(0.6)	(2.5)
Cluster 3	5.9	2.4	8.3	10.2	3.8	14.0
.	(0.3)	(0.1)	(0.4)	(0.7)	(0.2)	(0.9)
Cluster 4	3.4	1.4	4.7	9.2	3.4	12.6
	(0.2)	(0.1)	(0.3)	(0.8)	(0.3)	(1.1)

Note: This table shows the average minimum training cost for a worker in an occupation at high risk of automation, by country cluster and risk of acceptable occupation of destination. For example, the average *total* minimum training cost for a worker in a high risk occupation in Cluster 1 is USD 10 800 (PPP) if all occupations of destination (“All destinations”) are considered and USD 17 000 (PPP) when restricting occupations of destination to those with a low or medium risk of automation (“Only low or medium risk of automation destinations”).
Costs are per worker: “Direct” is the education cost of retraining workers; “Indirect” refers to the foregone wages during the training period; “Total” denotes the sum of the direct and indirect costs. Standard errors in parentheses. The composition of clusters is given in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017)

The aggregate training cost is obtained by multiplying the number of workers who are currently employed in high risk of automation occupations and perform a majority of tasks that can be automated (Nedelkoska and Quintini, 2018[18]) by the per-worker, occupation-specific cost of moving to a “safe haven”, and by summing over all occupations at high risk of automation.

The aggregate cost can be expressed as percentages of a country’s yearly GDP or total annual secondary and tertiary current education expenditure (Figure 3.14).[4] It should be noted that these ratios compare costs of training that is likely to occur over several years (as numerator), with a yearly aggregate (as denominator). Transitions may require training spells longer than a year, if no acceptable transition to low- or medium risk of automation occupations can be reached after a small or moderate training effort. Furthermore, workers and employers may decide to spread the training time over several years, to reconcile (part-time) work and training. Lastly, policies should not target all workers at high risk of automation at the same time and within one year, as technology spreads and is adopted at different paces in different countries, industries and companies.

The aggregate cost of moving to a "safe haven" varies between countries from less than 0.5% to over 2% of one year of GDP, of which around 30% is accounted for by direct costs and 70% by indirect costs. Direct costs range from 3% to more than 20% of yearly education expenditure, depending on the country.

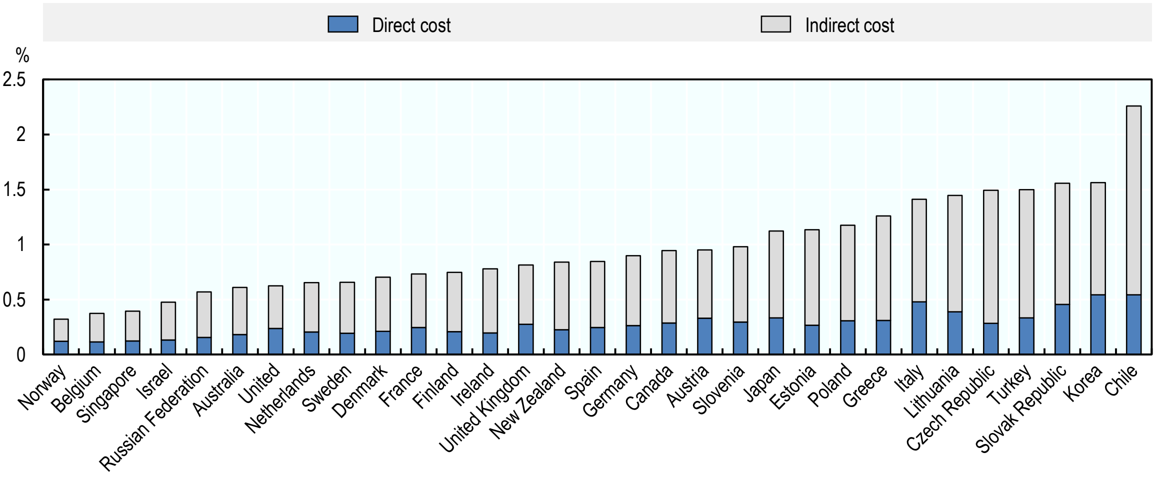
The indirect component of the cost of training coming from foregone workers' wages represents approximately 70% of the per-person total cost, and is therefore larger than the direct cost of undertaking the training spell in the education system itself. This result underlines the importance of enabling individuals to be able to train and learn while continuing to work, to lower the indirect cost of moving and mitigate the overall cost of education and training policies that can help workers move away from occupations at high risk of automation.

Estimates are heterogeneous across countries, no matter the denominator chosen to rescale them. Cross-country variation mainly originates from differences in (i) median wages across clusters, which underpin indirect costs; (ii) country-specific education expenditures per student; (iii) average skills distances for occupations at high risk of automation and the set of acceptable occupations of destinations they support, which depend on the cluster countries belong to; and (iv) the proportion of workers in the country employed in occupations at high risk of automation.

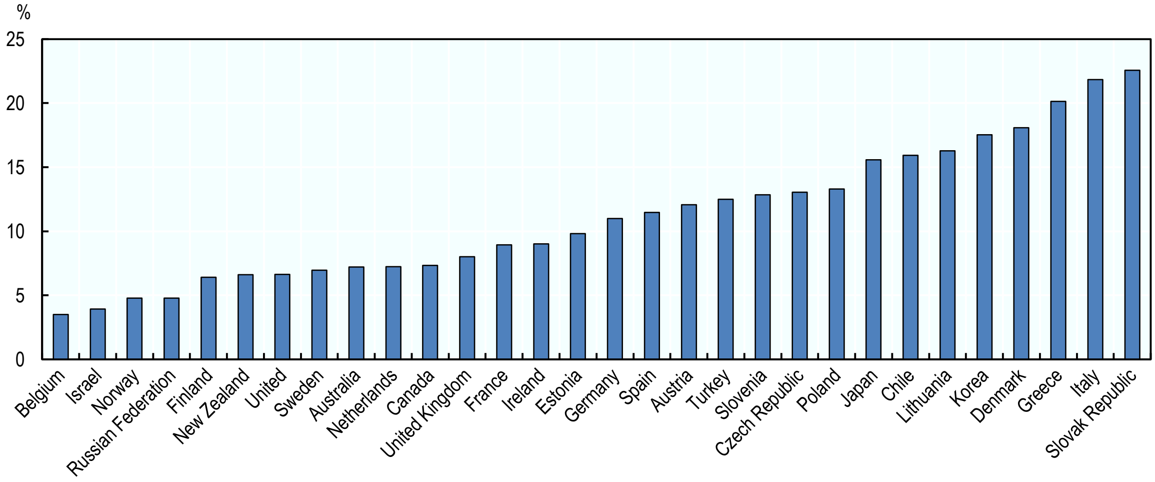
The share of employment in occupations at high risk of automation is a major driver of the aggregate costs (Table 3.5). Countries with a high share of employment in those occupations (Chile, Greece, Italy, Korea, Slovenia and Turkey) feature the highest aggregate costs. Differences in direct and indirect costs between countries play a smaller role in explaining differences in costs. In addition, as the direct cost of education and training relies on education expenditure per student and the analysis builds on an average skills return to education, countries with high per student education expenditure have a higher estimated direct cost of training.

Figure 3.14. The aggregate cost of moving to a “safe haven”, lower bound estimate, by country

Total cost as a share of one year of GDP



Direct cost as a share of one year of education expenditure



Note: The graphs show the aggregate costs of the minimum training effort necessary to help workers in occupations at high risk of automation find at least one acceptable occupation of destination that is not at high risk of automation. The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) (Box 3.4).These costs are computed only for the proportion of workers currently in jobs at high risk of automation, which varies by country and occupation (Nedelkoska and Quintini, 2018[18]).
Costs are represented as a percentage of yearly GDP and annual total expenditure for secondary and tertiary education (ISCED levels 3 to 8) in the country. The construction of the direct and indirect costs is explained in Box 3.4.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, OECD (2018[20]), OECD, *Structural Analysis (STAN) Database*, http://oe.cd/stan and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017).

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Table 3.5. Factors driving aggregate cost of moving to a "safe haven", by country

🟦 First quartile (high performance)
▨ Second quartile
⬜ Third quartile
⬛ Fourth quartile (low performance)

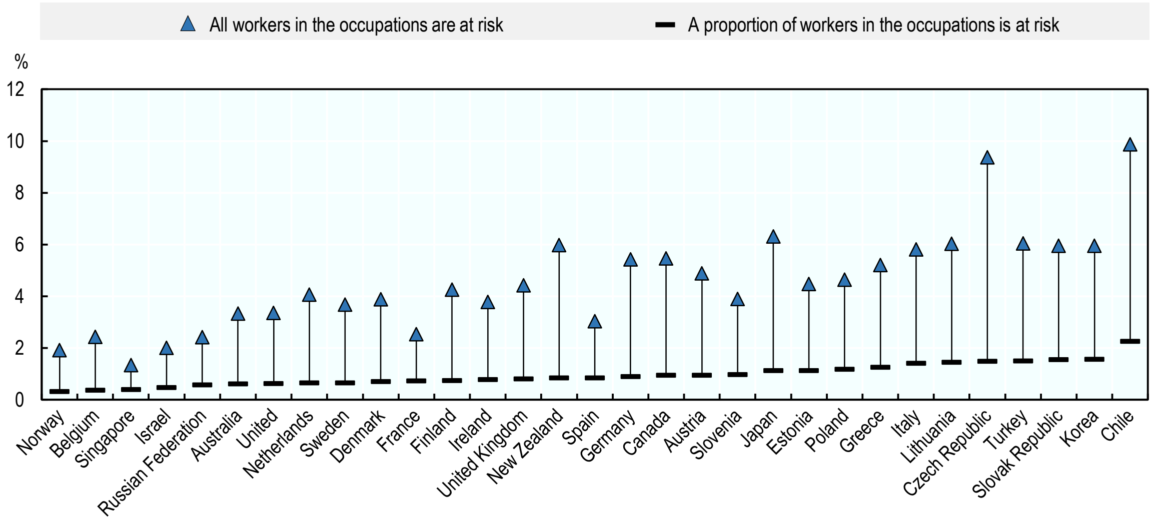
	Share of employment currently in jobs at high risk of automation	Indirect cost component (wages as a share of GDP)	Direct cost component (training cost as a share of GDP)	Training duration component	Total cost as a share of GDP
Australia	🟦	▨	▨	⬜	🟦
Austria	⬜	⬜	⬜	🟦	⬜
Belgium	🟦	⬜	⬜	🟦	🟦
Canada	🟦	▨	▨	⬜	⬜
Chile	⬛	▨	▨	⬛	⬛
Czech Republic	⬜	⬜	⬜	🟦	⬛
Denmark	▨	⬛	⬜	🟦	▨
Estonia	▨	⬛	⬛	▨	⬜
Finland	🟦	⬛	⬛	🟦	▨
France	⬜	🟦	🟦	▨	▨
Germany	▨	🟦	🟦	🟦	⬜
Greece	⬛	▨	▨	⬛	⬜
Ireland	▨	⬛	⬛	⬜	▨
Israel	🟦	⬜	⬜	▨	🟦
Italy	⬛	🟦	🟦	⬛	⬛
Japan	⬜	🟦	🟦	🟦	⬜
Korea	⬛	▨	▨	▨	⬛
Lithuania	⬜	⬛	⬛	⬛	⬛
Netherlands	▨	▨	▨	🟦	🟦
New Zealand	▨	⬛	⬛	⬜	▨
Norway	🟦	⬜	⬜	🟦	🟦
Poland	⬜	▨	▨	▨	⬜
Russian Federation	🟦	🟦	🟦	⬛	🟦
Singapore	⬜	⬜	⬜	▨	🟦
Slovak Republic	⬜	⬜	⬛	⬛	⬛
Slovenia	⬛	⬛	⬛	▨	⬜
Spain	⬛	▨	🟦	▨	▨
Sweden	🟦	⬜	⬜	🟦	▨
Turkey	⬛	🟦	🟦	⬛	⬛
United Kingdom	▨	🟦	▨	⬜	▨
United States	▨	🟦	🟦	⬜	🟦

Note: For example, the total cost for Australia is low (in the first quartile of the cost distribution). Australia has a low share of employment in occupation at high risk of automation and low direct and indirect cost of training while it belongs to a cluster with large distances across occupations.
The indirect component corresponds to average foregone wages as a share of GDP and the direct component to average education and training cost as a share of GDP. Calculations of the share of employment currently in jobs at high-risk of automation is explained in Box 3.4. "Training duration" corresponds to the average training duration required to reach "safe havens" in the minimum training needs scenario.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, OECD (2018[20]), OECD, *Structural Analysis (STAN) Database*, http://oe.cd/stan and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017).

The cost greatly depends on the number of workers who may need to participate in education and training. Estimates in Figure 3.14 assume that only a proportion of workers employed in occupations at high risk of automation are actually at risk and would need training, which gives a lower-bound estimate. Assuming that all workers in these occupations are at risk gives an upper-bound estimate of the education and training cost (Figure 3.15). This would correspond to a longer-term situation in which those occupations tend to be almost fully automated and to disappear. In such a case, the training costs entailed by moving to a "safe haven" would be fivefold, with the average overall cost ranging from 1% to 10% of GDP depending on countries.

Figure 3.15. Lower bound and upper bound estimates of the cost of moving to a "safe haven"

% of GDP, upper-bound and lower-bound estimates



Note: The graph shows the aggregate costs of the minimum training effort necessary to help workers in occupations at high risk of automation to find at least one acceptable occupation of destination that is not at high risk of automation, as a percentage of GDP and considering two different sets of workers. For the lower bound estimates, the cost only includes workers currently in jobs at high risk of automation, while the upper bound includes all workers currently employed in occupations at high risk of automation. The blue bar therefore represents the range of possible cost between upper- and lower-bound estimates. The proportion of workers at high risk of automation in an occupation is from Nedelkoska and Quintini (2018[18]). The construction of the total costs is detailed in Box 3.4.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, OECD (2018[20]), OECD, *Structural Analysis (STAN) Database*, http://oe.cd/stan and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017).

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Many uncertainties surround these estimates. As discussed in methodological sections of this chapter and further in Box 3.3, the methodology relies on several assumptions that affect the size of the estimated effects. In particular, there are large uncertainties concerning the number of occupations that would be less in demand in the future and the share of workers who might need to change occupations, which are crucial drivers of these estimates. Some workers in occupations at high risk of automation may never be displaced by automation, because the nature of their job evolves, or because automation pervades economies in unexpected ways. For these reasons, lower and upper bound estimates could be different from those in this analysis.

This approach also assumes that workers complete their education and training programmes and that these programmes are successful in raising skills. There is no data on the completion rates of workers and adults. However, data on students (and therefore on youth) show completion rates of 75% for upper secondary education and 72% for tertiary education. By assuming fully efficient education and training programmes with full completion rates, the analysis tends to under-estimate the cost.

The estimates proposed thus far mostly relate to the cost of training individuals to endow them with the cognitive skills needed in the occupation of destination. Different occupations, however, require workers to acquire several task-based skills, e.g. management and communication skills or ICT skills. Occupational distances in such task-based skills are accounted for in the analysis since it is assumed that, in all the scenarios considered, workers can only move to occupations with a given distance in such task-based skills (Table 3.2). However, cost estimates only include those related to bridging cognitive skills distances.

Information from Eurostat's Continuing Vocational Training Survey (CVTS) can be used to tentatively assess the extra resources needed to enable workers to gain some job-specific skills needed to move to different occupations. This survey collects data on the employer-based training of workers.[5] Training types include general and professional IT, management, team working, customer handling, problem solving, office administration, foreign languages, literacy, numeracy, communication and technical job-specific skills. However, only a small share of employers provide training in literacy and numeracy skills. The average participant across all countries covered received 26 hours of training in 2015.

This survey does not break down cost data by type of skills. Furthermore, those data are not at the occupational level. Finally, those data cannot be used to assess the skills distance that may be bridged by participating in those training opportunities. For these reasons, the same cost needs are assumed for all workers regardless of the type of skill gap to be filled and of the occupations of origin and destination. These estimates do not include the indirect cost incurred by employers as workers generally continue to receive their wages while training on the job.

The extra cost component calculated on the basis of CVTS data can be added to the country-level cost of training workers to move from occupations at high risk of automation to occupations at medium or low risk. The top-up cost is calculated as the country-specific cost of training per participant as reported in the CVTS, multiplied by the number of individuals at high risk of automation who are working in the country. The extra cost component amounts to 0.06% to 0.3% of GDP on average across the considered countries (Andrieu et al., 2019[12]). This extra cost is small because the training duration is short according to this survey.

What type of training is required to move away from the risk of automation?

In addition to the need for upskilling in general cognitive skills (literacy and numeracy), occupations at high risk of automation are predominantly in need of training in non-cognitive skills, such as management and communications as well as self-organisation. They also require some training in ICT (Table 3.6). This is mainly because occupations at risk of automation perform mostly routine tasks, while management, communications and self-organisation are more difficult to automate.

Table 3.6. Relative task-based skills training needs involved for acceptable transitions to occupations at low or medium risk of automation

For occupations at high risk of automation, in the scenario with the smallest training need necessary to identify such transition

	ICT skills	Advanced numeracy skills	Accountancy and selling skills	Managing and communication skills	Self-organisation skills
Cluster 1	16	12	14	29	29
Cluster 2	23	13	12	33	19
Cluster 3	20	7	11	38	24
Cluster 4	22	9	15	31	23
All countries	22	10	16	33	20

Note: These tables display the relative minimum training need in terms of task-based skills necessary to help workers in occupations at high risk of automation to find at least one acceptable occupation of destination that is not at high risk of automation. For example, when all countries are considered together, for workers in occupations at high risk of automation to move to an occupation at low or medium risk of automation, the minimum training need would include upskilling mostly in managing and communication skills (33%), ICT skills (22%) and self-organisation skills (20%) and to a lesser in accountancy and selling skills (16%) and in advanced numeracy skills (10%).

Task-based skills are explained in Box 2.3 in Chapter 2. The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.3. Low automation risk occupations correspond to occupations with an automation probability below 30%, medium automation risk: between 30% and 70%, high automation risk: over 70%. Acceptable transitions are defined in Table 3.2. The composition of clusters is given in Table 3.1.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

Policy implications

Mitigating and sustaining the cost

The analysis in this chapter gives an indication of the cost of education and training needed to help workers move away from the risk of automation. These costs can be sizeable, even if they do not need to be sustained all in the short run or for all workers together.

The most important general policy implications of the analysis are to reaffirm the importance of:

- *Policies encouraging learning and working at the same time* through flexible education and training programmes and informal learning. Two-thirds of the estimated training cost comes from the indirect cost of foregone wages, so important savings could be made by enabling learning and working at the same time. First, flexible training options can be combined with work, for example through broader use by firms of open education and massive open online courses (MOOCs) (Chapter 5). Second, working environments and practices that facilitate learning by doing, learning from co-workers and other forms of informal learning can help workers develop the skills they needed as jobs evolve, while entailing little indirect and direct costs. Conversely, sending workers back to formal education is unrealistic on a large scale and would entail large costs.

- *High-quality initial education for all* to equip all future workers with a solid mix of skills, including a strong readiness to learn. Young people leaving education with low basic skills may become trapped in low-skilled occupations at high risk of automation, with a large cost of moving to another occupation if they lose their jobs. As well as limiting the number of students who drop out, policies can ensure that vocational education and training programmes include a strong component of cognitive skills in addition to job-specific skills. Improving the efficacy of educational institutions and the quality of education and training services would lower the direct cost of these policies.

To make it easier for workers move to jobs, an array of policies are needed, all of which require important monetary resources from policy makers. These include policies shaping initial education, skills development, life-long learning, support for worker re-deployment and improved social protection. Resources for industrial and regional policies should be taken into consideration, too, because the concentration of job transitions and the adoption of technologies vary among industries and regions. However, most governments already spend a significant share of their budget on those areas. The effort needs to be on developing a better co-ordinated and more comprehensive approach to facilitate lifelong learning and occupational and geographical mobility (Chapter 6).

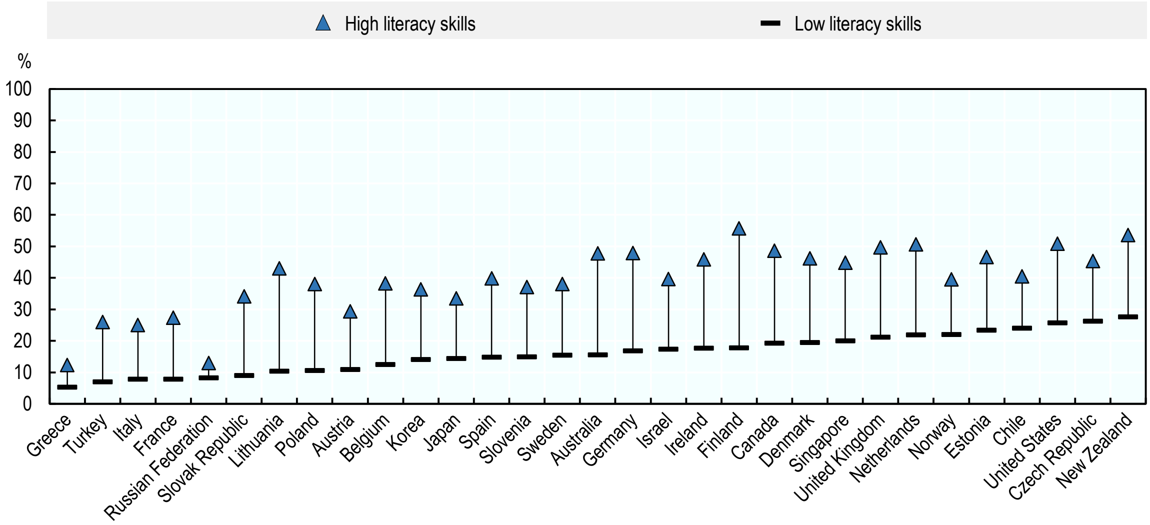
Improving the design and targeting of on-the-job training programmes

Overall, this analysis in this chapter shows that it is important to ensure that workers in occupations at risk of automation, especially those in low-skilled occupations, participate in education and training so they can change occupations and find a “safe haven”. However, these workers are less likely to participate in training than workers in occupations with a lower risk of automation (Nedelkoska and Quintini, 2018[18]). More generally, workers with lower skills levels participate less in on-the-job training than more skilled workers (Figure 3.16).

This analysis also show the need for training that helps workers develop a mix of skills, including cognitive, ICT and social and emotional skills, to make it easier for them to switch occupations. Policies that aim to develop task-based skills through learning or training on the job are sometimes not enough to help workers change jobs. Such policies need to be complemented by policies that aim to develop general cognitive skills, through specific programmes or by enabling workers to go back to formal education. Employers mainly provide training on job-specific skills, however, (Figure 3.17) and few workers go back to formal education in most countries because options to combine work and study are scarce.

Figure 3.16. Participation in on-the-job trainings by skill level

Share of workers with low or high literacy skill levels who have participated in on-the-job training over the 12 months before the survey, by country



Note: Share of workers answering "Yes" to the question "During the last 12 months, have you attended any organised sessions for on-the-job training or training by supervisors or co-workers?", for those with low (at or below *Level 1*) or high (*Level 4/5*) literacy skill levels. Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Overcoming the barriers to participate in adult learning

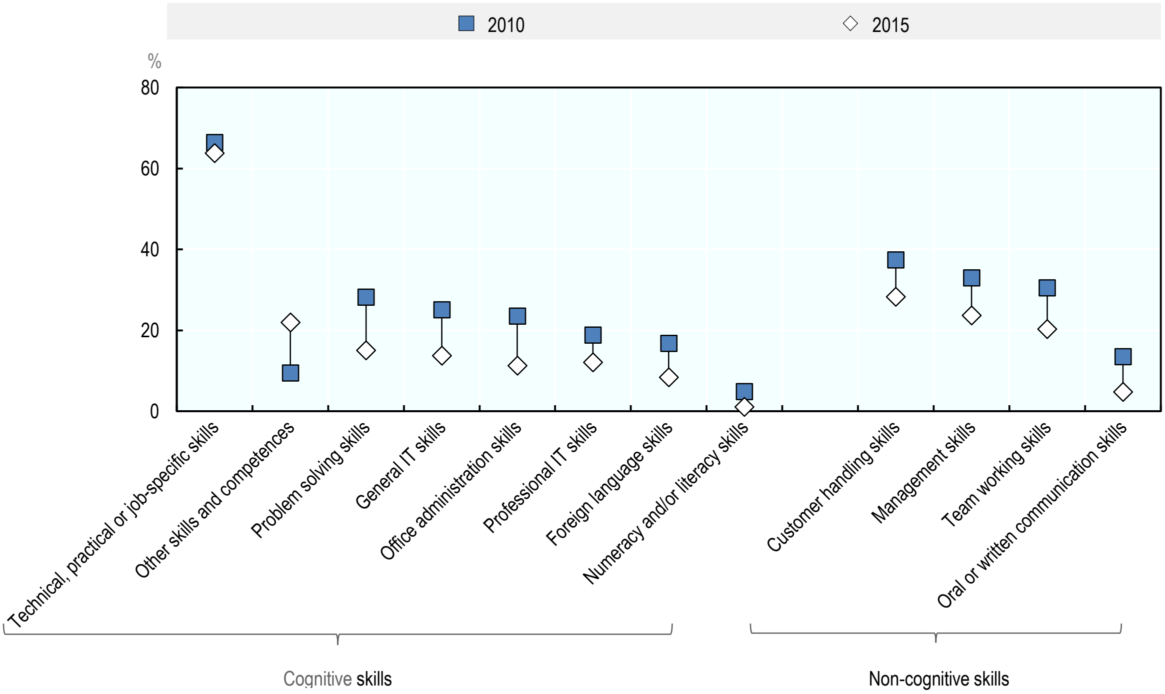
There are many barriers to participation in adult learning, including financial disincentives, time constraints, and the motivation and willingness to learn (Chapter 6).

The analysis in this chapter sheds light on the possible financial incentives of occupational mobility by comparing wages in occupations of origin and destination. An average worker in a significant majority of occupations at high risk of automation would, on average, experience a median hourly wage increase when moving to the closest set of "safe havens" (Figure 3.18). In fact, there is a somewhat decreasing relationship between initial wage and average wage change, implying that workers with smallest wages would possibly have the greatest financial incentives to retrain. Thus for most workers in these occupations, the financial burden of training would at least be partly compensated by an increase in wages in the future occupation.

However, this wage gain is an average and compares hourly wages not annual wages. Actual wage changes will depend on several other factors, such as number of hours worked, geographical location and worker preferences. In addition, the analysis does not incorporate the fact that if more workers try move to the same groups of occupations, raising labour supply for these occupations, wages may decrease. Workers in occupations that appear not to experience positive wage changes will find it much harder to afford and be willing to train. In such cases, workers may be willing to incur small wage losses if moving from a highly automatable occupation to a lower risk occupation appears to imply greater job stability.

Figure 3.17. Main skills targeted by vocational training in enterprises

European Union OECD countries, share of employers providing training related to each type of skills



Sources: Eurostat (2010[21]) and (2015[22]), *Continuing Vocational Training Survey (CVTS)*, https://ec.europa.eu/eurostat/web/education-and-training/data/database.

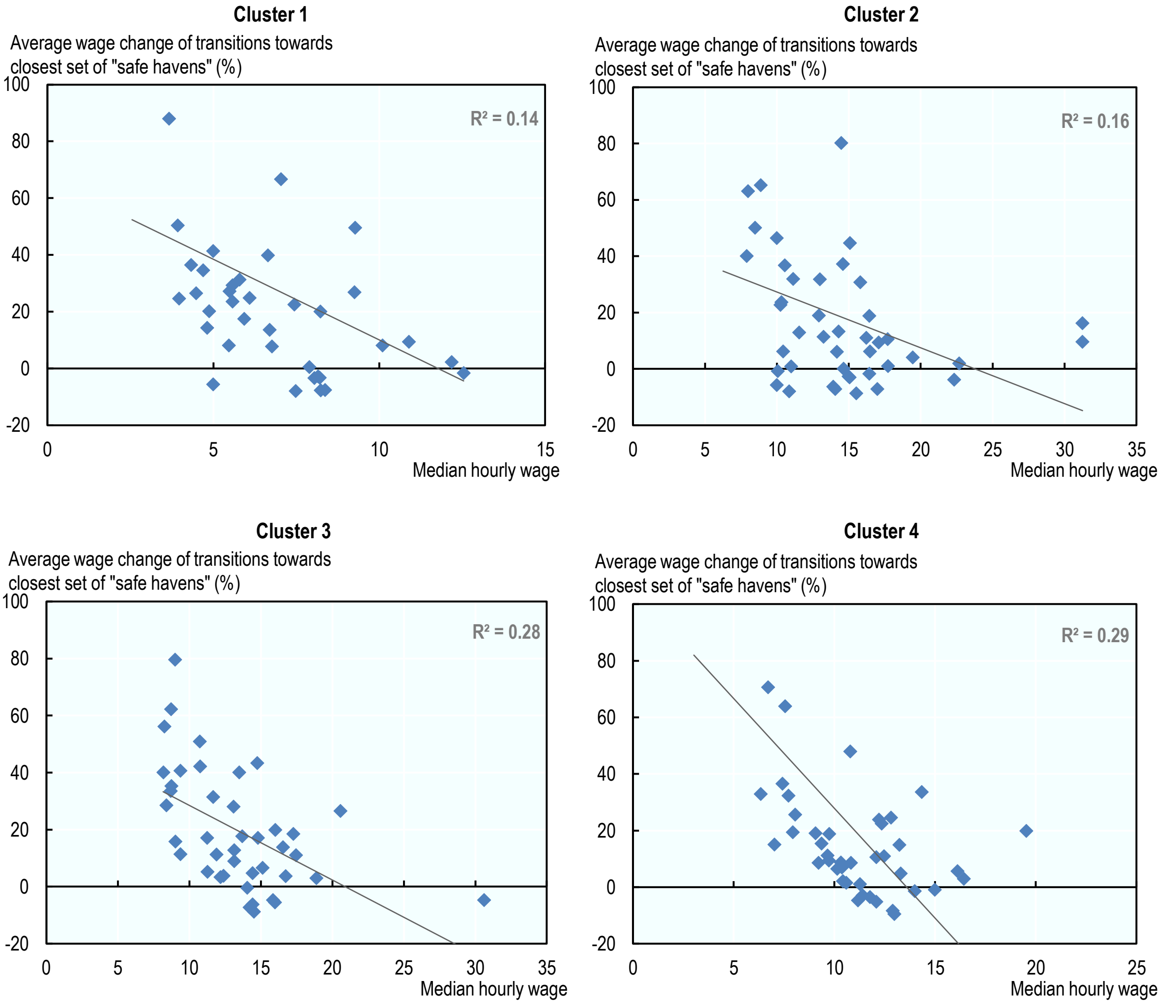
StatLink https://doi.org/10.1787/888933973665

Raising educational attainment?

Most of the occupations at high risk of automation have a majority of workers with at most a post-secondary non-tertiary degree (Figure 3.19). Only a few occupations have a majority of workers with a tertiary education degree. This is the case for all country clusters, though the magnitudes vary slightly.

However, raising educational attainment and enrolling more people in tertiary education can be costly and is not necessarily a good solution as having a tertiary degree does not guarantee having the required skills (Chapter 6). In addition, the analysis in this chapter finds that moving to a "safe haven" from occupations at high risk of automation that have a predominantly tertiary-educated workforce does not appear to require particularly lower average training durations than other occupations (Figure 3.20). Many of these occupations require small training needs, just like predominantly non-tertiary educated occupations.

Figure 3.18. Average wage change induced by transitions to minimum training need "safe havens"



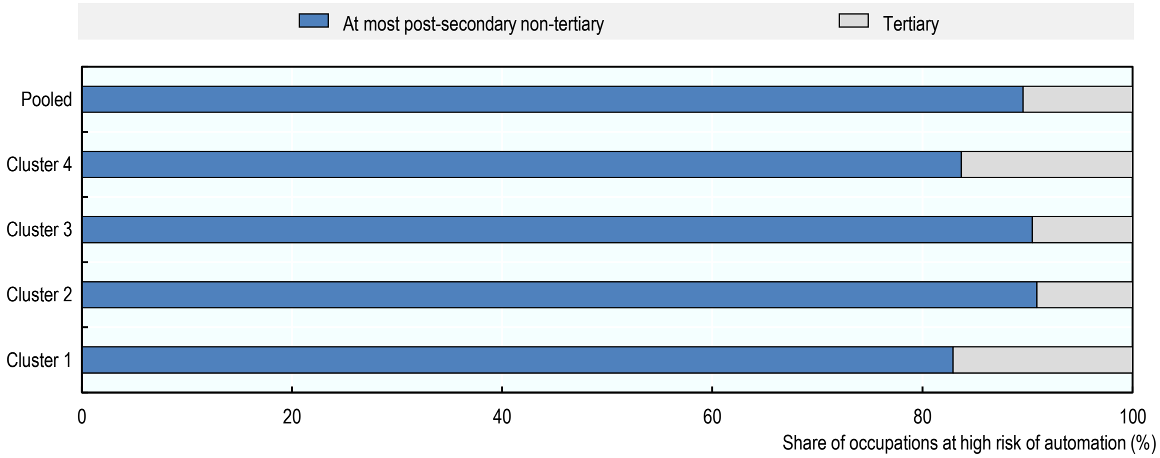
Note: For each cluster, these figures plot the relationship between high-risk occupations' average hourly wage change implied by transitions to the closest set of "safe havens" and their median hourly wage. In all clusters, the relationship is downward sloping, suggesting that, on average, the lower-paid a high-risk occupation the greater the wage change implied by moving to "safe havens". The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4. The composition of clusters is given in Table 3.1. The R^2 corresponds to the share of the variation in average hourly wage changes that is explained by median hourly wage.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973684

Figure 3.19. Most common education level of occupations at high risk of automation

Occupations' education level is that which represents the majority of workers



Notes: For each country cluster, each bar shows the share of occupations at high risk for which a majority of workers have at most a post-secondary non-tertiary degree or a tertiary degree. For example, in cluster 3, 90% of occupations at high risk have a majority of workers with at most a post-secondary non-tertiary degree while this share is 83% in cluster 1.

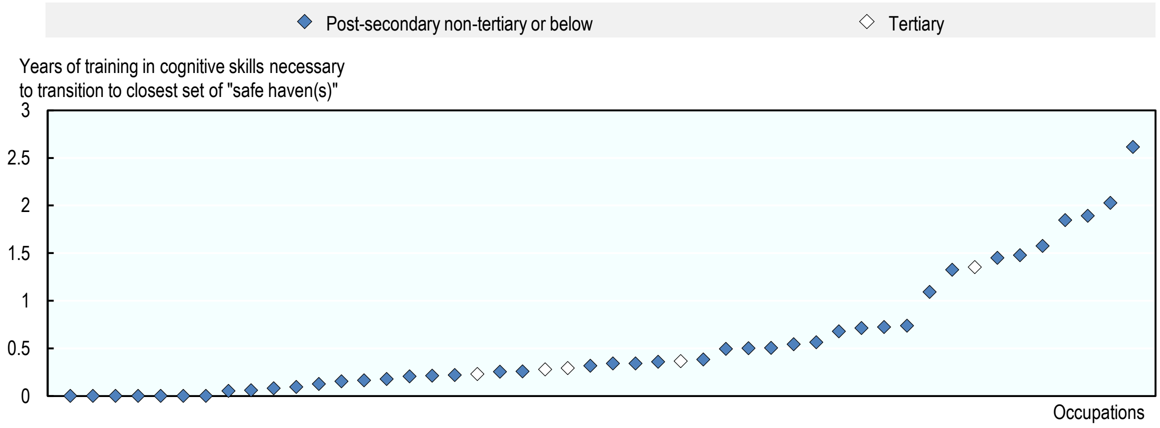
Occupations at high risk of automation have an automation probability greater than 70%. The risk of automation of origin occupations is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973703

Figure 3.20. Occupations' average number of years of training for closest "safe havens", by education level

Occupations at high risk of automation are ranked by the average number of years of training necessary to transition to closest set of "safe havens"



Notes: Calculations are based on results when countries are considered together. The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]).

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973722

Young versus older workers

Older workers may find it more difficult than young ones to switch jobs, on average. They have a higher incidence of long-term unemployment and lower hiring rates, take longer to get back to work after an unemployment spell and experience larger earning losses after being displaced (OECD, 2013[11]). As the average age of the population in OECD countries keeps increasing, occupational mobility is likely to represent a greater challenge for older workers and, consequently, a significant concern for policy makers.

Older workers also tend to be over-represented in occupations for which larger education and training costs are needed to help workers move jobs (Andrieu et al., 2019[12]). This finding is not driven by the fact that older workers may be in occupations with higher wages and therefore incur higher indirect costs of training.

Licensed occupations

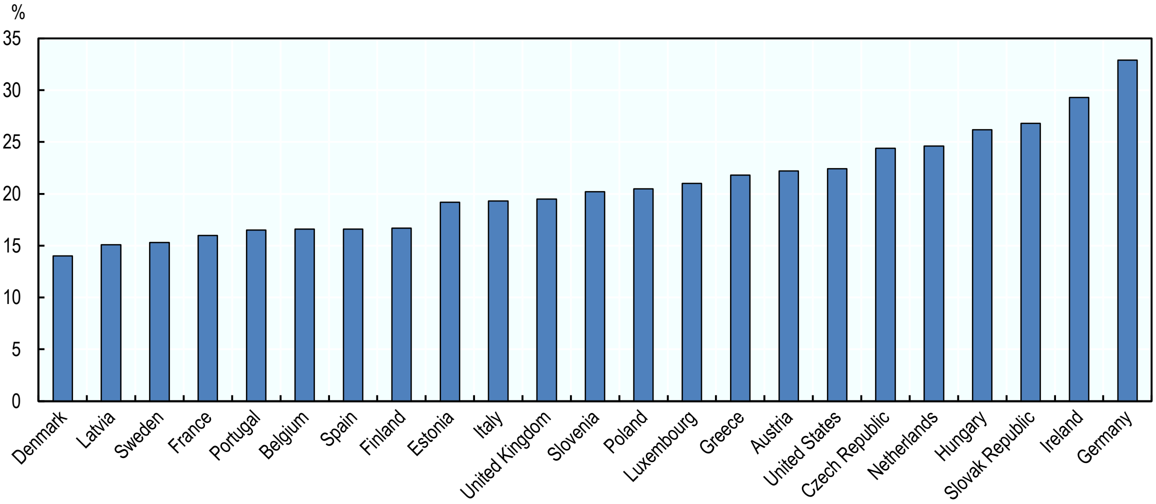
Occupational licensing – the legal requirement to obtain a licence to undertake a certain occupation – is intended to protect consumers through higher quality and skill requirements. Yet it can also constitute a barrier to occupational mobility and career progression. Workers wishing to switch to a licensed occupation may find the requirements too time-consuming or financially burdensome. Conversely, workers in licensed occupations may find it costly to switch occupation as they would lose the benefit of the licence they have obtained. Licensed occupations may tend to experience lower employment growth, therefore affecting the allocation of workers (Kleiner, 2017[23]). This is of significant importance since about 25% of US workers and 22% of EU workers hold a license (Figure 3.21). Regulatory authorities could consider which occupations should legitimately require a license (legal restriction) rather than a certificate (no legal restriction), which can just equally act as a signal for skill and quality.

Sharing the cost of training between stakeholders

As discussed in this and other chapters of this publication, improving the design and efficiency of a range of policies can reduce the overall cost if a significant share of workers need to be retrained to move occupations and escape the risk of unemployment.

In addition, however, it is likely that countries may need to increase their investment in education and training, to face changes in skills requirements and higher demand for workers with a well-rounded set of skills. This raises the question of how to share the burden of the cost between governments, firms and workers themselves. There is no single answer to this question, as it depends on countries' cultures, financial positions, institutions and arrangements, but a debate on this question needs to take place. At the moment, the allocation of education expenditure between public and private sources varies greatly among countries (Figure 3.22).

Figure 3.21. Percentage of licensed workers in selected OECD countries in 2015



Note: This figure displays the percentage of licensed workers in selected OECD countries in 2015. The percentage of licensed workers is computed as the percentage of employed individuals aged 15 and over (16 for the United States) who require a licence to work.
Sources: For all countries except the United States, estimates come from Koumenta, M. and M. Pagliero (2017, p. 28[24]), "Occupational licensing in the European Union: Coverage and wage effects", http://sites.carloalberto.org/pagliero/Pagliero_Koumenta_wages.pdf (accessed on 08 June 2018), based on questions from the EU Survey of Regulated Occupations. For the United States, the estimate comes from the Bureau of Labor Statistics (2017[25]), *Table 49. Certification and Licensing Status of the Civilian Noninstitutional Population 16 years and Over by Employment Status*, https://www.bls.gov/cps/cpsaat49.htm (accessed on 29 August 2018), based on questions from the Current Population Survey.

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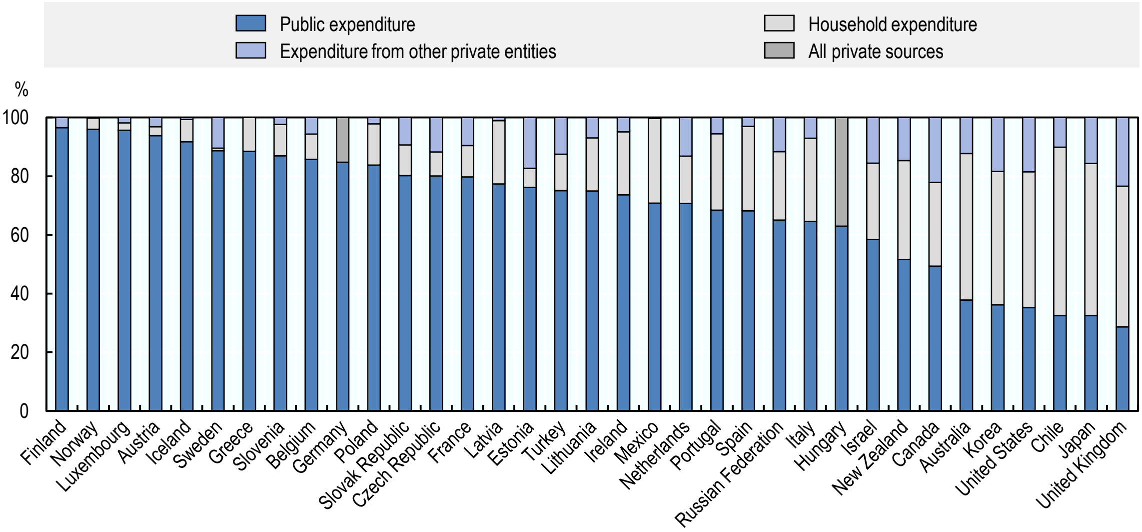
Figure 3.22. Distribution of public and private expenditure on tertiary education in 2015



Note: Excluding international sources: Canada, Chile and Korea. Data from 2016: Chile.
Source: OECD (2018[26]), *Education at a Glance 2018: OECD Indicators*, https://dx.doi.org/10.1787/eag-2018-en, Figure C3.2.

StatLink https://doi.org/10.1787/888933973760

Summary

This chapter investigates how education and training policies can help workers move occupations, while maintaining them in quality jobs that make the best use of their skill sets. In addition, it sheds light on the magnitude and type of training needed to help workers move away from occupations at high risk of automation, and the associated costs.

Not all occupations at high risk of automation require the same policy effort. Some of these occupations are close to others that require similar skills but have a smaller risk of automation. Simply providing information about options for transitions or making a small retraining effort may be sufficient to help workers in these occupations find a "safe haven". The main policy effort needs to focus on workers in occupations at high risk of automation that are distant from other occupations in terms of their skills requirements and tasks contents. Hence, this chapter suggests directions for better targeting the policy effort at workers who need it the most.

The chapter also estimates the possible costs of education and training policies to help workers move from occupations at high risk of automation to "safe havens". The costs are substantial for several countries but need not all be sustained immediately, as workers in occupations at high risk of automation will not all move to a "safe haven" at the same time.

There are several ways to reduce this cost. Important savings could be made by enabling learning and working at the same time, improving the efficacy of educational institutions, and improving the quality of education and training services more broadly. Learning and working at the same time can be encouraged through policies that promote flexible education and training programmes, the use of open education and massive open online courses (MOOCs) by firms, and the adoption of working organisation practices that favour co-operation, learning from co-workers and other forms of informal learning. Special training efforts may be needed for low-skilled workers, who tend to benefit less from technical change and adapt to it less well than highly skilled workers. Curricula may need to be adapted more frequently and to reflect a holistic approach to skills in order to cater for the numerous competencies that are demanded from workers. More broadly, additional efforts may be needed to bridge the information gap so that employers, workers and educational institutions are aware almost in real time of the successful skills mixes needed on the labour market.

Workers, employers, education institutions and governments all have roles to play in responding to the reskilling and upskilling challenge, including its financial aspect. How these stakeholders will meet the demand for resources, however, remains an open question. The split in the costs of retraining could reflect the sharing of the costs and benefits of mobility, be they in the form of changes in wages, productivity of labour, or tax receipts. Employers, for instance, could be encouraged to invest in transferrable (rather than only firm-specific) skills, to establish work-education partnerships with the education sector, or to create training programmes that are better tailored to individual workers.

Notes

[1] Assuming an employment gain of 10 in one occupation is achieved by 15 hires of workers coming from another occupation and 5 separations towards other occupations, then the net occupation mobility is 10, the gross mobility is 20 and the excess reallocations are 10.

[2] The third cognitive skill measured in PIAAC, problem solving in technology-rich environments, is not included in the analysis because many individuals with generally lower literacy and numeracy skills did not take the assessment test for problem solving. Excluding these individuals from the analysis would lead to a strong selection bias. In addition, France, Italy and Spain have not participated in the assessment tests for problem solving and would be excluded from the analysis when using problem solving as a third cognitive skill.

[3] Data are from 2015 or 2014 when 2015 is not available. When core services expenditure are missing, they are replaced: for primary to secondary expenditure by total expenditure minus the OECD average ancillary services (Canada, Denmark, Greece, Ireland, Japan, New Zealand); for tertiary expenditure by total expenditure minus countries' expenditure on R&D activities when they exist (Finland, Greece, New Zealand) or OECD average (without outliers) expenditure on R&D activities otherwise (Denmark, Japan). For Canada for which tertiary education expenditure per student is missing, the average expenditure of other countries in the same cluster is applied.

[4] Education expenditure by ISCED2011 level by private and public institutions is sourced from the Education at a Glance (2017) database and refers to 2015 or 2014. Data on GDP are sourced from the OECD Structural Analysis (STAN) database and refer to the year 2014.

[5] The CVTS collects data on vocational training within EU enterprises with at least 10 or more employed persons and belonging to a certain group of economic activities.

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Annex 3.A. Methodological Assumptions

Annex Table 3.A.1. Main hypothesis and their implications for the estimates

	Hypothesis	Motivation	Implications for the estimates
1	Training costs are estimated based on bridging cognitive skills shortages, and only partly on task-based skills shortages.	Data which would allow assessing how much an hour of education/training would yield in terms of all task-based skills included in the analysis is lacking.	This hypothesis underestimates training cost, as occupational transitions can imply shortages in both cognitive and task-based skills. However some task-based skills are likely picked up while developing cognitive skills (e.g. the correlation between numeracy and ICT and advanced numeracy is high).
2	The cost of training is derived using information on education expenditures rather than actual training costs. In particular, data from OECD Education at a Glance on per-pupil core expenditure for secondary and tertiary education is used. Moreover, in the absence of reliable data on adults' learning abilities, education and training are assumed to cost the same for all individuals, regardless of their age.	This assumption does *not* imply that training needs to be provided by the formal education sector. Education expenditure data are used as reference costs, in the absence of more complete information about training costs. No international comparable data exist on adult training. For European countries, the Eurostat's Continuing Vocational Training Survey (CVTS) gives information on the cost per hour but no information on the outcome of training is provided. These data show a higher hourly cost of training than data on education from OECD Education at a Glance but the hourly cost is likely inflated given that the training performed is of a short term nature (average of 36 hours per year).	This hypothesis may overestimate training costs if: • Education expenditure figures include a range of expenses which do not apply to adult learning/training or include the development of some skills that is not needed for occupational transition. • Adults learn faster/more effectively than young people, because of experience or knowledge accumulated on the job. This hypothesis may underestimate training costs if: • Alternative data sources like the CVTS are used to estimate yearly costs, though CVTS figures refer to short duration training programmes. • Education and training systems enjoy "economies of scale" relative to training provided in different shapes or forms (e.g. on a firm-by-firm basis). This may depend also on different bargaining power and purchasing of big versus small companies, the type of training providers, etc.

	Hypothesis	Motivation	Implications for the estimates
			• Adults learn more slowly than young individuals.
3	Working and learning at the same time is ruled out: when in training, individuals are assumed to not work.	Learning here is intended as structured learning aimed to improve cognitive skills. Improving such an assumption would require having information about the time that working individuals can devote to structured learning.	This hypothesis overestimates training costs, as allowing the possibility to learn and work at the same time would decrease the indirect cost of training, which accounts for a large share of total costs.
4	Training is effective, in that all individuals acquire the necessary skills within the estimated training spell duration.	The assumption that all individuals are able to learn and acquire skills is a necessary condition without which the training time needed to bridge the skills shortages between any two occupations cannot be estimated. Data on type, duration and success rates of adult learning/training is lacking.	This hypothesis may underestimate training costs if training is only partially effective, i.e if only a part of the adult population is able to learn or if adults learn to different extents.
5	All individuals manage to bridge the same cognitive skills shortage within a certain training spell.	The regression based approach adopted (which controls for a number of covariates known to affect learning) is needed to translate skill shortages into a training duration. While accounting for all individuals' learning specificities would be impossible, availability of relevant data might help improve the accuracy of the current estimates.	This hypothesis may overestimate training costs if adults learn at a faster pace than estimated and underestimate training costs if adults learn at a slower pace than estimated.
6	All countries' education systems have the same effectiveness.	Up-to-date and comparable data on the effectiveness of education systems is lacking.	This hypothesis may overestimate training costs for countries that have relatively more effective education and training systems and underestimate training costs for those featuring relatively ineffective education and training systems.
7	Workers transit directly to a different occupation, without going through an unemployment spell.	The objective of the work presented in this chapter is to find alternative occupations and estimate the cost of moving workers away from jobs at "high" risk of automation. The focus is not on workers who are already unemployed. If data were available about previous occupations, unemployment spell characteristics and skills depreciation over time, among others, the proposed analysis could be used to also inform the discussion on how to help individuals move out of unemployment.	This hypothesis may overestimate training costs for: • Individuals moving out of unemployment, as the opportunity costs would be lower than those estimated for workers. This hypothesis may underestimate training costs if: • Unemployment spells depreciate workers' competencies and therefore increase the skills shortages to be bridged.
8	The opportunity cost is represented by foregone wages.	Given hypotheses 3 and 7, workers are assumed to transit to the next occupation upon receiving training while being formally employed in the occupation of origin. This entails that they receive their salary while on training.	This hypothesis may overestimate training costs if workers can learn or train while working or receive a lower wage while training.

	Hypothesis	Motivation	Implications for the estimates
9	The analysis refers to “acceptable” transitions, which are identified on the basis of skills shortages and excesses as well as wage conditions.	Estimates rely on available information. Information on a number of aspects known to impact occupational transitions (e.g. location, industry structure, family setting, workers’ preferences, contract type, etc.) are not available and thus cannot be taken into account.	This hypothesis may overestimate training costs if: • Workers are willing to accept greater unused human capital and wage losses to transition away from a “high” risk of automation. This hypothesis may underestimate training costs if: • Acceptable transitions are unavailable in a certain region and workers would need to train for a longer spell.
10	Wage decreases of more than 10% are considered unacceptable.	This figure corresponds approximately to the average annual earnings loss of workers one year after displacement in 5 OECD countries. Workers facing high risks of displacement may accept larger wage cuts.	This hypothesis may overestimate training costs if: • Workers are willing to accept higher wage cuts. This hypothesis may underestimate training costs if: • 10% is a too high wage pay cut to accept, and workers need to train for longer spells to find acceptable transitions.
11	The labour market will be able to absorb workers in one or more of the occupations of destination identified as acceptable transitions.	For simplicity, the analysis does not take into account general equilibrium effects. Indeed, as workers progressively move out of certain occupations to others, labour demand and returns in the occupations of destination will adjust to the inflow and outflow of workers.	How these effect would increase or lower the overall cost of retraining, will depend on the design of the general equilibrium model.

Chapter 4. Skills for a digital society

Digitalisation transforms the way people live, bringing both opportunities and challenges. This chapter investigates social changes arising from the ubiquity of smartphones and Internet connections, the types of skills people need to make the most of these changes, and how education and training policies can best provide those skills. The "digital divide", which initially concerned gaps in Internet access, increasingly concerns the different ways people are able to use the Internet and the benefits they derive from their online activities. Skills appear to be an important factor behind these differences. A wide range of policies is needed to ensure that the use of technologies does not exacerbate inequalities between individuals or hinder well-being. Schools have a key role in teaching values and skills to combat cyberbullying and excessive use, while local communities can help older individuals to develop basic digital skills.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

The digital transformation affects many aspects of daily life. Information and communication technologies (ICTs) provide more than an infrastructure that can facilitate access to information and to private and public services. They influence the way people interact, communicate, learn, build trust in others, participate in the democratic process, and spend their time. E-commerce is shaping consumers' behaviour and time use, the retail industry and even how cities look. The time that people spend on their smartphones and the implications for their social life and well-being have now become crucial questions.

As parents, consumers and citizens, people need skills to access information and perform tasks that are done through the Internet while preserving their privacy and security. If people have the necessary skills, digitalisation offers considerable potential not only to disseminate knowledge, improve political engagement and increase efficiency of public services, but also to enable new forms of leisure.

If technology spreads more quickly throughout daily life than people's skills develop, however, some individuals may be left behind or may feel isolated. Older people are especially vulnerable to such risks. Differences in how individuals use digital devices and the Internet tend to exacerbate existing inequalities. To prevent digital divides from emerging or expanding, it is vital to understand better the minimum skills that people require.

The digital transformation can increase well-being but also creates new risks, such as over-consumption, unwilling exposure of personal information or cyberbullying. Exposure to such risks may harm children's performance at school and the development of their skills. The increasing digitalisation of many services, public (e.g. e-government, e-health) and private (e.g. e-banking), can lessen people's opportunities to interact with others, reducing their sense of participating in and belonging to communities and societies. How does technology change social interactions and affect the development of social and emotional skills? These are compelling questions in an increasingly digitalised society.

This chapter investigates the types of skills people need to make the most of the digital society. It considers how policies can ensure that individuals benefit from new online opportunities while avoiding the risks attached to them. The chapter first describes the emergence of a "digital society" and the rapid increase in the type of activities that can be performed on line. Then it discusses how the digital divide in access has progressively been replaced by a divide in the ways individuals use the Internet and the benefits they derive from their online activities.

The chapter performs new empirical analyses to investigate which cognitive skills shape digital divides in terms of use and outcomes. It discusses how participation in online activities can expose people to risks or increase their well-being, while looking at the specific role of skills in these relationships. Finally, it derives some policy implications.

Evidence is lacking on many aspects of how new technologies change the way people live, what benefits and risks digital societies bring, and how education and training policies need to be adapted to address these changes. This chapter investigates these keenly debated questions on the basis of the information and data that is available. To obtain a more comprehensive analysis, however, more information would be needed, including data on a broader range of skills, such as advanced digital skills and social and emotional skills. Moreover, this chapter discusses several issues where existing evidence is not yet conclusive, including the implications of digitalisation for well-being, the exposure of individuals to privacy risks, cyberbullying, and the relationship between technology use, mental health and social ties. While cognitive, social and emotional skills are likely to shape how technology affects individuals' well-being, more research is needed to gauge the effect of technology on many societal dimensions.

The main findings of this chapter are:

- The Internet provides people who would otherwise be isolated with opportunities to communicate and obtain access to information. As broadband access has developed, however, a lack of skills has become an increasingly important reason why some people do not have Internet at home.
- As Internet use evolves, divides between individuals concern more and more the ways they use the Internet and the benefits they obtain. An increasing number of activities can be performed on line, some of which are complex, and people go on line at increasingly younger ages.
- The ways people use the Internet tend to reproduce existing inequalities. Low-performing students are less likely than top performers to look for information on line or read the news, for example, while more skilled individuals are more likely to follow online courses.
- Four profiles of Internet users emerge from the analysis presented in this chapter, based on data from some European countries: i) diversified and complex use; ii) diversified but simple use; iii) use for practical reasons; and iv) use for information and communication. Lacking basic literacy and numeracy skills is a barrier to performing activities online and belonging to any of these profiles. Lacking basic problem-solving skills in technology-rich environments is a barrier to performing diversified and complex activities.
- Having higher cognitive skills – either literacy, numeracy or problem-solving skills in technology-rich environments, or a mix of these – significantly augments the probability that people will move from using the Internet mostly for information and communication to a diversified and complex use, taking other determinants into account. However, skills do not appear to play a significant role in shifting Internet use from information and communication to other types of relatively simple uses.
- Having a good level of cognitive skills also increases the likelihood that individuals perform activities to protect their privacy and security when they go on line. Different sets of cognitive skills have different impacts on the type of actions individuals take to ensure their online security and privacy.
- The ubiquity of smartphones at an increasingly younger age may create new opportunities for children's cognitive stimulation but also bring new risks, such as cyberbullying and excessive use, which are often difficult to detect. Information on the impact of smartphones and tablets on mental health at various ages is still scarce. More highly skilled parents may be better prepared to guide children in their use of technology, especially as evidence shows that children tend to turn to parents when they encounter problems linked to online activities. To prevent the development and use of such technologies from exacerbating inequalities, educational institutions and teachers have an important role to play: they can both help detect such problems and teach values and knowledge that prevent risky behaviours. Policy makers could also consider a co-ordinated and comprehensive regulatory response to address the risks that children face on line.

- Little is known about the effects of technology use on mental health, the development of skills, and social interactions both with friends and strangers. Equally, individuals' capacity to make the most of digital technologies in their everyday lives is likely to be shaped by a range of skills that cannot be measured with existing methods, including the ability to navigate in an uncertain environment, conceptual understanding, the capacity to see the bigger picture and grasp what lies behind information, and the kinds of actions that can be taken online.
- Available data on cognitive skills suggest that countries differ significantly in how prepared their populations are for the digital transformation. Some, such as Israel, Korea and Slovenia have a high proportion of older adults lacking basic skills in literacy, numeracy and problem solving in technology-rich environments. In these countries, programmes need to target older adults and ensure social isolation does not increase with the development of new technologies. Local communities and associations can play a key role in developing people's digital skills and resilience.
- In some countries, such as the United Kingdom and the United States, the share of young people lacking basic skills is relatively high. In these countries, policies need to ensure education and training systems equip all young people with strong skills. Finally, in countries such as Chile and Greece, a large share of the whole population is lacking basic skills, requiring a comprehensive approach to boosting skills.

Participation in online activities

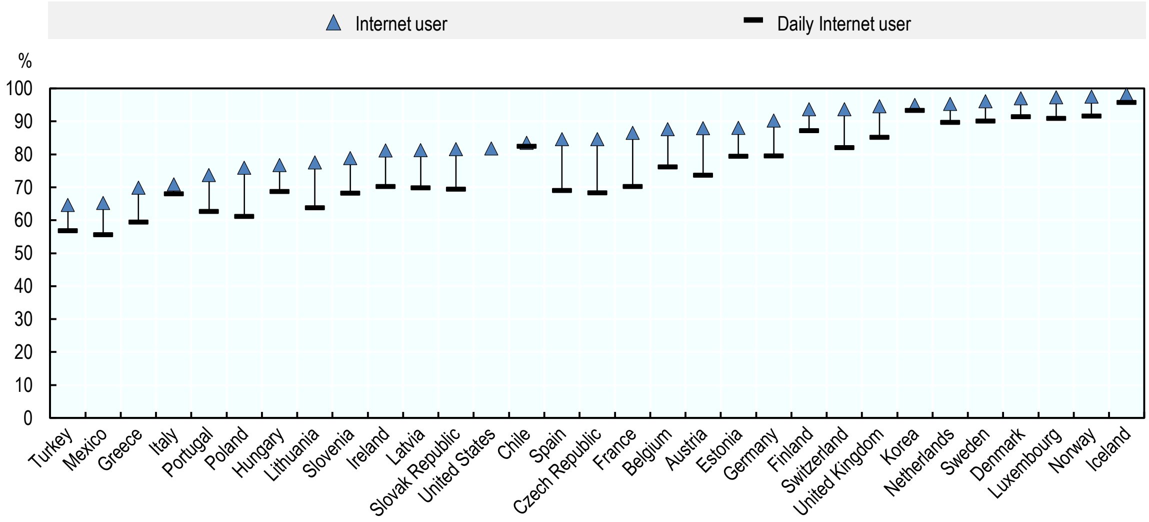
Across OECD countries, people go on line at increasingly younger ages. In 2015, two out of three students aged 15 in OECD countries with PISA data had accessed the Internet for the first time before they were 10; one out of five had done so before the age of 6 (OECD, 2017[1]). These numbers are likely to have further increased. Time spent by 15-year-olds on line increased between 2012 and 2015; on average across OECD countries students spent more than three hours on the Internet on a typical weekend day in 2015 (OECD, 2017[1]).

The pervasiveness of Internet use among 15-year-olds reflects ever higher use of the Internet and digital tools throughout society. In 2017, 76% of those aged 16-74 in OECD countries connected to the Internet on a daily basis and in several OECD countries, almost all individuals were daily Internet users (Figure 4.1). Disparities in Internet uptake across and within OECD countries remain, but Internet use has been rising steadily: in 2006, less than 60% of individuals went on line (OECD, 2017[2]), while more than 85% went on line in 2017.

ICTs have transformed daily lives. People go on line to look for jobs or accommodation, or to learn through online tutorials (Box 4.1). In recent years, the share of individuals going on line to become informed, use social networks, buy goods or interact with public authorities has steadily increased (Figure 4.2). As societies rapidly become digitalised, many emerging activities may not even be captured by data yet. Better access to the Internet and smartphones has enabled many individuals, including those who live in isolated areas or have low socio-economic status, to participate in many activities to which they might not otherwise have had access.

Figure 4.1. Internet users in OECD countries

Share of individuals aged 16-74, 2017



Note: Internet users are individuals who have used Internet in the last three months. Daily Internet users are individuals who have used Internet daily or almost daily in the last three months.
Source: OECD (2017[3]), *ICT Access and Usage by Households and Individuals Database*, http://oe.cd/hhind (accessed on 15 November 2018).

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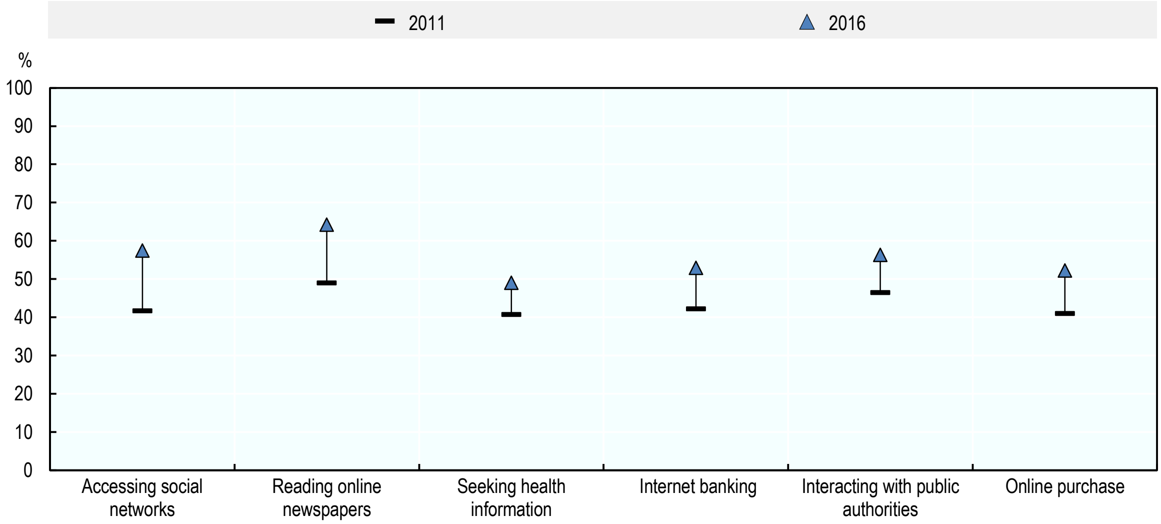
Figure 4.2. Participation in online activities in 2011 and 2016

Share of individuals aged 16-74



Note: Averages are computed over OECD countries with available data in both 2011 and 2016.
Source: OECD (2017[3]), *ICT Access and Usage by Households and Individuals Database*, http://oe.cd/hhind (accessed on 15 November 2018).

StatLink https://doi.org/10.1787/888933973798

Box 4.1. The emergence of new online activities

The Internet permeates every aspect of the economy and society: individuals connect not only with one another but also with businesses and public institutions, through multiple devices. As the uptake of activities such as sending e-mail or using social media reached a large majority of the population, other types of online activities have recently emerged and gained importance with the upskilling trend, new user needs and new business models.

E-health

E-health refers to the cost-effective and secure use of ICTs to support health and health-related fields. In 2017, across OECD countries, half of all individuals aged 16-74 accessed health information online – 58% of women and 46% of men, up from 40% of women and 32% of men in 2010. More and more people also use e-health services to make an appointment with a health practitioner. In 2016, 13% of Europeans used the Internet for this purpose, roughly a one-third increase since 2012 (OECD, 2019[4]). These behavioural changes are often related not only to increasing digital skills but also to the ageing of societies and the diversification of online service provision.

In addition, individuals are increasingly using mobile wireless technologies for public health, also referred as “m-health” (World Health Organization, 2017[5]). For example, the 2013 joint ITU-WHO initiative “Be He@lthy Be Mobile” harnesses the power and reach of mobile phones to educate people to make healthier lifestyle choices and hence prevent non-communicable diseases (heart disease, stroke, cancer, diabetes) by managing risk factors.

Platform-mediated services

Online platforms, such as Uber and Airbnb, facilitate interaction and (re-)intermediate transactions, partly or fully on line, by matching demand and supply of goods, services and information (OECD, 2016[6]). Platform service markets are often characterised according to aspects that may differentiate them from traditional markets, for example their potential to involve “collaboration”, “sharing” or the delivery of services “on demand”. Platform workers use an app or a website to connect customers with a diverse range of services, including ride hailing, coding and writing product descriptions.

In 2018, 23% of surveyed individuals in the European Union used services offered via collaborative platforms (Flash Eurobarometer 467, 2018[7]). Among these people, over half have accessed services in the accommodation (57%) and transport (51%) sectors, but few have accessed professional services (9%) or collaborative finance (8%). Furthermore, only 6% of Europeans have offered services via collaborative platforms.

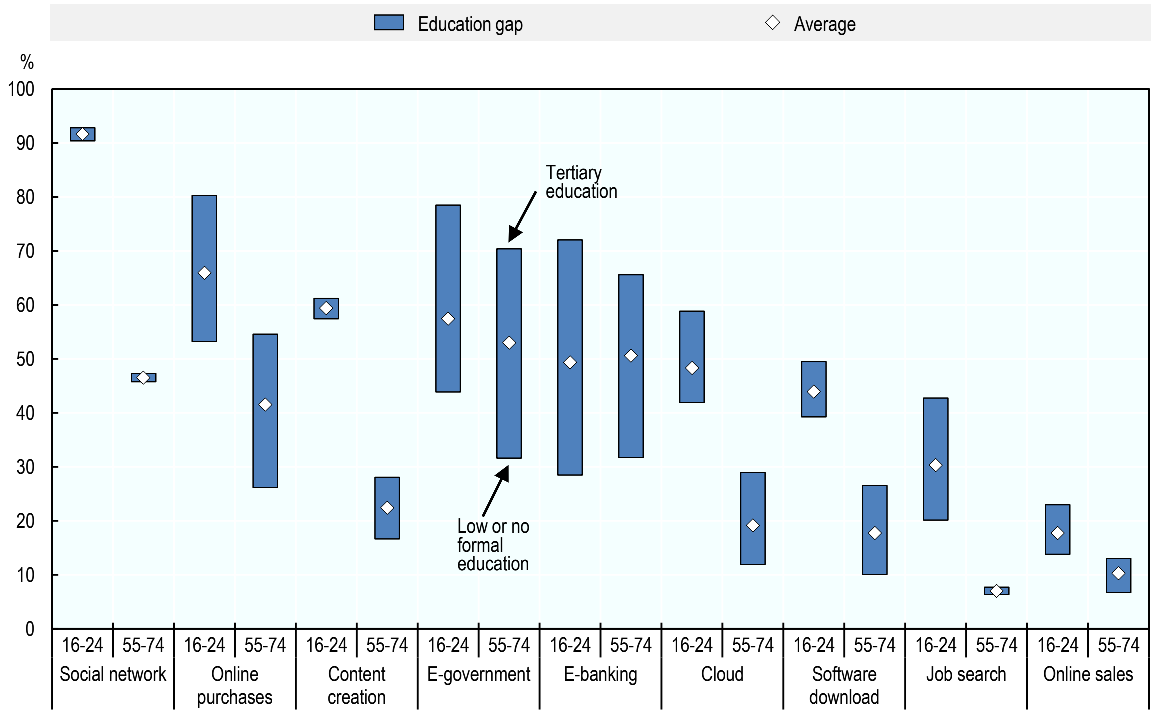
Sources: Campante, F., R. Durante and F. Sobbrio (2018[8]), “Politics 2.0: The multifaceted effect of broadband Internet on political participation”, http://dx.doi.org/10.1093/jeea/jvx044; Falck, O., R. Gold and S. Heblich (2014[9]), “E-lections: Voting behavior and the Internet”, http://dx.doi.org/10.1257/aer.104.7.2238; Flash Eurobarometer 467 (2018[7]), *The Use of the Collaborative Economy*, http://dx.doi.org/10.2873/312120; OECD (2019[10]), *How's Life in the Digital Age?: Opportunities and Risks of the Digital Transformation for People's Well-being*, OECD, Paris; OECD (2016[6]), *New Forms of Work in the Digital Economy*, https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DSTI/ICCP/IIS(2015)13/FINAL&docLanguage=En (accessed on 16 January 2019); OECD (2019[4]), *Measuring the Digital Transformation: A Roadmap for the Future*, https://doi.org/10.1787/9789264311992-en; World Health Organization (2017[5]), *mHealth: Use of Appropriate Digital Technologies for Public Health*, http://dx.doi.org/10.1371/journal.pmed.1001362.

The Internet also provides people with a new arena in which to engage in civic and political debates, to exchange ideas and to voice frustration (OECD, 2019[4]). In 2017, 11% of people in the European Union expressed opinions on civic or political issues via websites (e.g. blogs and social media). Across the OECD countries, several governments use ICTs to engage citizens not only to facilitate voting but also throughout the regulatory process (OECD, 2019[10]). The most frequent purpose is to gather feedback from the public on draft regulations and plans to change existing regulations. In parallel, civil and political participation is also affected by the Internet as an alternative information channel to the traditional media. The Internet shapes voters' exposure to information and voter turnout under certain conditions (Falck, Gold and Heblich, 2014[9]; Campante, Durante and Sobbrio, 2018[8]).

Many activities that were previously conducted in person, such as paying taxes or consulting a medical practitioner, are being progressively digitalised. Digitalisation offers easier access to services and goods, but also raises challenges in terms of inclusion: all individuals are not equally likely to take part in many of these new activities, especially as levels of trust in online environments vary. Young people engage more in many of these new online activities, as do those with tertiary education (Figure 4.3).

Figure 4.3. Diffusion of selected online activities among Internet users, by age and educational attainment

Internet users performing each activity as a percentage of the respective group, 2017



Note: For a given activity: (i) data are computed on the basis of the same group of OECD countries for both age categories; (ii) for both age categories, data relate to the average of all individuals ("Average"), the average of all individuals with low or no formal education, and the average of all individuals with tertiary educational attainment. For all activities, the average for all individuals relates to a number of OECD countries ranging from 23 to 27, according to data availability for both age categories. Tertiary education refers to ISCED levels 5 or 6 and above. Low or no formal education refers to ISCED levels 0 to 2.
Source: OECD (2017[3]), *ICT Access and Usage by Households and Individuals Database*, http://oe.cd/hhind (accessed on 15 November 2018).

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Age and education shape online participation differently. Younger people have a higher uptake of social networks, online purchases and content creation, but participation in e-banking or e-government is more influenced by education levels. Irrespective of their age, people with tertiary education are almost two times more likely to engage in e-banking or e-government than lesser-educated people. The more digitally skilled individuals are, the higher their satisfaction and perceived quality of e-government (Ebbers, Jansen and van Deursen, 2016[11]). As many governments increasingly digitalise their administrative services, many people will not be able to make use of such services if they lack the necessary skills.

These initial figures suggest that digitalisation offers many new opportunities for daily life and participation in society. However, not all individuals are equally positioned to take advantage of them.

From a divide in access to a divide in uses

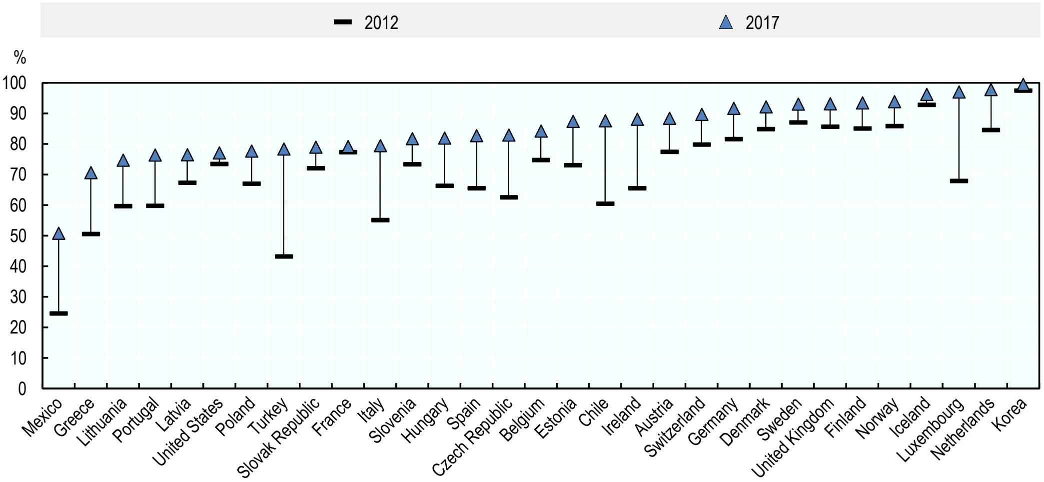
The digital divide has evolved from a divide in Internet access to a divide in how individuals use the Internet and the benefits they derive from their online activities. Skills play a key role in the emergence and evolution of digital divides.

Sources of the divide in access

The digital divide in terms of access has progressively narrowed across OECD countries. Access to broadband Internet connections has steadily increased in the past years, giving people better online experiences. In 2017, 85% of households across OECD countries with available data had access to broadband Internet, a 20% rise from 2012 (Figure 4.4). Cross-country digital divides persist nevertheless. Despite a large catch-up rate between 2012 and 2017, connectivity remains a problem in Mexico, where only one in two households has access to broadband Internet. In France, the Slovak Republic and the United States, access to broadband has stagnated in the past years and remains below the OECD overage.

Figure 4.4. Home access to broadband Internet in 2012 and 2017

Share of households with broadband Internet access at home



Source: OECD (2017[3]), *ICT Access and Usage by Households and Individuals Database*, http://oe.cd/hhind (accessed on 15 November 2018).

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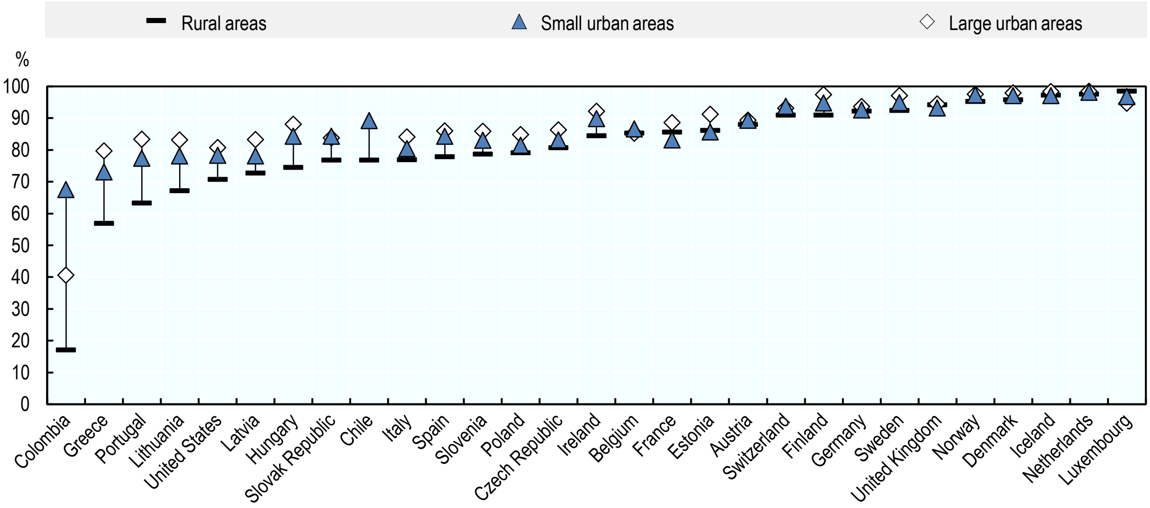
Divides in digital access run within countries as well as between countries. In many OECD countries, rural areas still lag behind urban areas in terms of Internet broadband access (Figure 4.5). In Chile, Greece, Lithuania and Portugal, the connectivity gap between households in rural areas and those in large urban areas exceeds 10 percentage points. Similar divides persist across regions (Chapter 6). Such digital exclusion patterns are likely to exacerbate other social and economic inequalities.

Figure 4.5. Internet broadband access in rural and urban households

Share of households with broadband Internet access at home in each category, 2017



Source: OECD (2017[3]), *ICT Access and Usage by Households and Individuals Database*, http://oe.cd/hhind (accessed on 15 November 2018).

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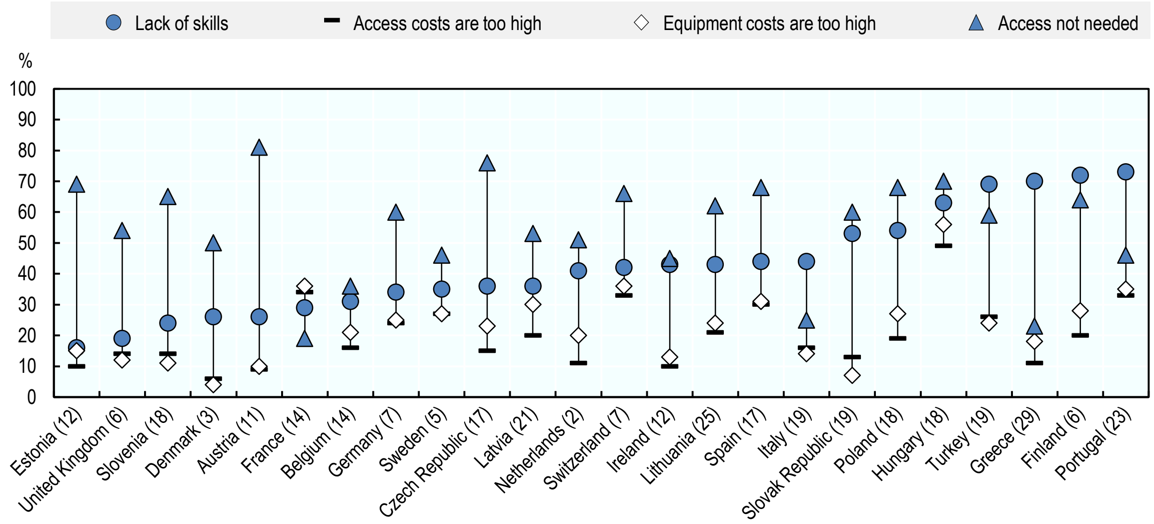
However, access to digital infrastructure is limited not just by unaffordable costs or insufficient infrastructure investments. Among OECD countries with available data, 43% of households give as a main reason for their lack of Internet access a lack of skills or knowledge, such as not knowing how to use a website or considering its use too complicated (Figure 4.6). In countries like Greece or Portugal, where more than one in five households are not connected to the Internet, more than 70% of households report such a lack of skills. When skills are not the most recurrent reason for lacking Internet access, most households report that they do not need access because content is not useful or not interesting. Such a rationale is likely to reflect an inability – because of inadequate skills – to make the most of the opportunities offered by the Internet.

A lack of skills has become a major factor behind the digital divide in access in many European countries (Figure 4.7). As the costs of connecting to the Internet at home have fallen, more and more households in countries such as Greece, Lithuania and Turkey are invoking their lack of skills to explain the absence of an Internet connection in their household. When compared with all other reasons reported by households to explain why they have no Internet connection (including access and equipment costs, privacy concerns, access elsewhere), lack of skills has experienced the most sizeable rise since 2010 on average across European countries (European Commission, 2018[12]).

Figure 4.6. Reasons for not having Internet access at home

Share of households without Internet at home reporting a given reason for not having Internet access, 2017



Note: The share of households without Internet access at home is reported in parentheses next to the country names. Several reasons can be reported by the same household.
Source: Eurostat (2017[13]), *European Community Survey on ICT Usage in Households and by Individuals*.

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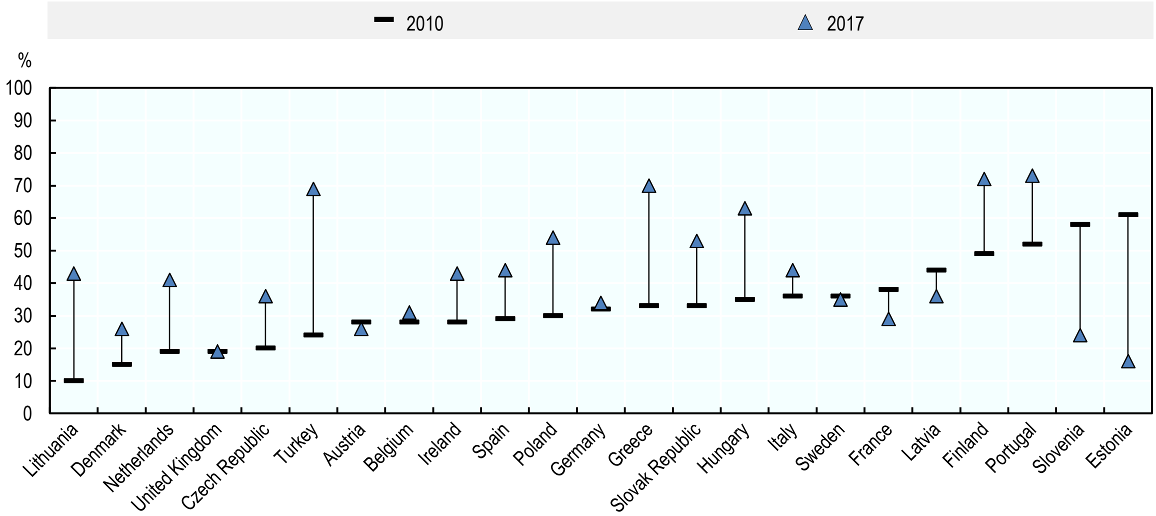
Figure 4.7. Households without Internet access because of lack of skills, in 2012 and 2017

Share of households reporting not having Internet access at home because of lack of skills among households with no Internet access at home



Source: Eurostat (2017[13]), *European Community Survey on ICT Usage in Households and by Individuals*.

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Divides in uses and benefits of Internet access

Access to the Internet and digital infrastructure is merely the first step for digital inclusion. Even when people have access to the Internet, there may still be differences in how they use the Internet and the benefits they obtain. Differences in access have declined over time, but differences in uses and the results of Internet use are becoming increasingly important (van Deursen and van Dijk, 2014[14]; van Deursen and Helsper, 2018[15]; Hargittai and Hsieh, 2013[16]).

Most of the factors that shape digital inequalities in access, such as gender, socio-economic background, labour force status, geography or skills (Fairlie, 2004[17]; Dewan and Riggins, 2005[18]), can equally shape digital inequalities in use (Robinson, Dimaggio and Hargittai, 2003[19]; Hargittai and Hsieh, 2013[16]; Demoussis and Giannakopoulos, 2006[20]). The share of low-educated individuals with no Internet access has decreased in the last decade, but some studies find that low-educated individuals use the Internet more for recreational than for instructional activities in comparison with the highly educated (van Deursen and van Dijk, 2014[14]). In a similar vein, disadvantaged students play online games, chat or participate in social networks as much as advantaged students, but they are less likely to read news or get practical information from the Internet (Figure 4.8). Overall, data from PISA (2015) show that in OECD countries, socio-economic and demographic characteristics shape the ways 15-year-olds use ICTs in their leisure time.

Differences in people's digital activities may not matter if they have no effect on other outcomes. There is significant evidence, however, that most digital uses reproduce and even amplify non-digital inequalities (van Deursen et al., 2017[21]). If low-skilled people use the Internet more for chatting and entertainment whereas highly skilled people look for jobs, follow courses or make health appointments on line, the use of Internet coupled with the lack of skills risks amplifying existing inequalities. Thanks to their Internet use, the highly skilled obtain more opportunities to expand their knowledge, find better jobs more easily or secure faster access to healthcare. Having the needed skills and level of education can protect against the risk of a digital divide and can also avoid exacerbating other divides.

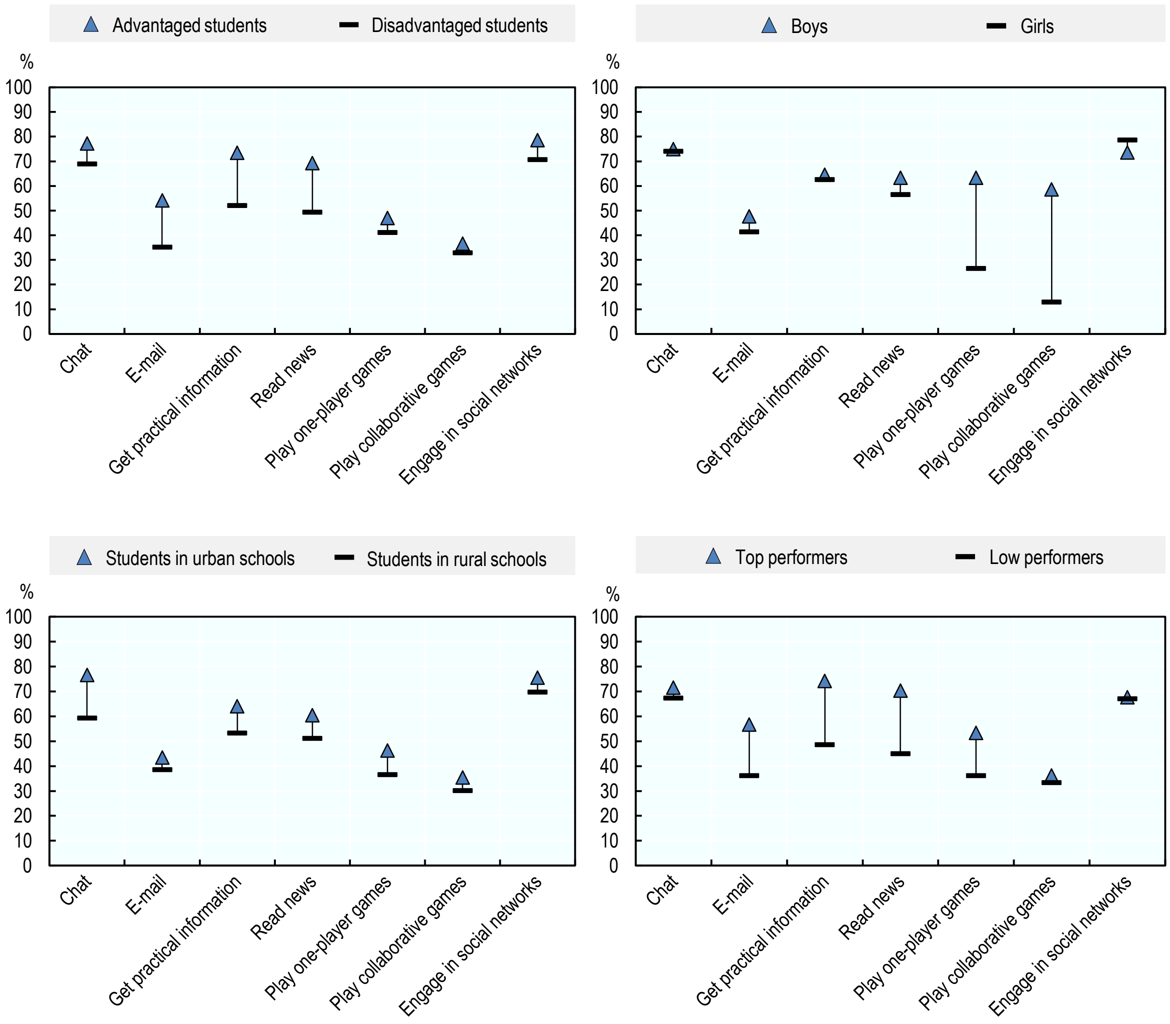
Which cognitive skills to bridge digital divides in use?

People with more skills can make better use of the Internet and online activities. To design policies that bridge the digital divide, it is necessary to understand what types of skills help people to get the most out of the Internet, and how important those skills are vis-a-vis other determinants.

To investigate the relationship between skills and participation in online activities, and how skills can help close digital divides, data from two surveys was related through statistical matching (Box 4.2). The European Community Survey on ICT Usage in Households and by Individuals (CSIS) is carried out annually by Eurostat, the statistical office of the European Union. It gathers detailed data on a range of activities performed online, such as reading and sending emails, looking for information, buying goods and services, participating in social networks, and learning online. The Survey of Adult Skills, a product of the OECD Programme for the International Assessment of Adult Competencies (PIAAC), includes information on cognitive skills (literacy, numeracy, problem solving in technology-rich environments) measured through assessment tests.

Figure 4.8. Uses of digital devices outside of school, by students' characteristics

Share of students reporting to make a given use of digital devices outside of school at least once per week



Note: Shares are computed on average over all OECD countries participating in the PISA ICT questionnaire. Activities are unfolded on line. Students are considered to be socio-economically disadvantaged if their values on the PISA ESCS index are among the bottom 25% within their country or economy. Students in rural schools are students whose school is located in "a village, hamlet or rural area with fewer than 3 000 people" while students in urban schools are students whose school located in a city of over 100 000 people. Students who are low performers are students who score at less than Level 2 in the reading, mathematics and science assessments. The level 2 is considered to be the baseline level of proficiency reading, mathematics and science. Students who are top performers are students who are proficient at Level 5 or 6 in reading, mathematics and science.

Source: OECD calculations based on OECD (2015[22]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

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The robustness of analyses performed on a matched database inevitably depends on the quality of the statistical matching between the two datasets, which in turn is largely determined by the information available in the two datasets and the similarity of this information. The two datasets used for this analysis share a fair number of variables on ICT usage but a limited number of individual characteristics. Limited information on educational level and occupation in the CSIS dataset may have lowered the quality of the match. For these reasons, the analysis presented in this section should be considered as exploratory and results should be taken with caution.

Identifying profiles of Internet users

As most people perform several activities online, the analysis applies a clustering method to identify profiles of Internet users (Box 4.3). Those profiles take into account the number and the distribution of activities performed. Four clusters or profiles of Internet users emerge.

These four profiles of Internet users first differ in the average number of activities performed (Figure 4.9). People belonging to profile 1 perform most of the activities (8 activities on average among the 11 considered in the analysis) while those belonging to profile 4 perform the smallest number (slightly less than two on average). Hence, profile 1 reflects a diversified use of the Internet while profile 4 captures a much narrower use. Profiles 2 and 3 fall in between. People in profile 2 also display a relatively diversified use of the Internet, with more than four activities on average, while those in profile 3 show a less diversified use. Some activities emerge as being rarely performed and therefore draw a line between profiles. This is the case of learning, e-finance and, to a lesser extent, creative activities that can be considered more complex.

More specifically, the following Internet user profiles can be identified:

- *Diversified and complex use*, corresponding to profile 1. People in this profile perform on average the largest number and greatest variety of activities. They carry out the biggest share of online tasks linked to e-finance, learning and creativity, activities that are performed by the smallest range of individuals and that can also be considered more complex.
- *Diversified and simple use*, corresponding to profile 2. Individuals in this profile perform a range of activities, like those in profile 1, but fewer linked to finance, creativity and learning. Their main activities online revolve around communication, social networks, access to information and entertainment.
- *Use for practical reasons*, corresponding to profile 3. People in this profile use the Internet in diverse ways, albeit less so than individuals in profiles 1 and 2. They use Internet mostly for communication, looking for information, e-health and e-banking.
- *Use for communication and information*, corresponding to profile 4. Individuals in this profile make the most specialised use of internet, mainly using communication tools and accessing the Internet to obtain information. These latter two activities combined make up for 70% of all activities performed on line by individuals in this user profile.

Socio-demographic characteristics appear to be related to the type of Internet uses (Figure 4.10). People whose online activity is “diverse and complex” are the most educated in the sample, a majority of them employed and of prime age. Among them, 39% are tertiary educated and 41% have completed upper-secondary education. Employed people are over-represented in this profile – they constitute 70% of all individuals with a “diverse and complex use”. Three out of four individuals in this Internet user profile are aged 25 to 55, showing that young people (aged 16 to 24) and those aged 55 to 64 are less likely to make diverse and complex use of Internet.

Box 4.2. Statistical matching of the Survey of Adult Skills (PIAAC) and the European Community Survey on ICT Usage in Households and by Individuals (CSIS)

For this report, statistical matching was performed to generate a unique dataset that includes both information on cognitive skills measured through assessment tests (from the Survey of Adult Skills, PIAAC) and indicators of ICT usage by individuals (from the European Community Survey on ICT Usage in Households and by Individuals).

Statistical matching integrates two (or more) datasets drawn from the same population (D'Orazio, Di Zio and Scanu, 2006[23]) to explore the relationship between variables of interest that could not be jointly observed. If dataset A contains Y and dataset B contains Z, and both datasets contain a set of common variables X, statistical matching allows a unique dataset to be created that contains X, Y and Z (Rubin, 1986[24]). In this case, Y and Z are the variables of interest and X are control variables.

Matching methods that only rely on the common X variables to integrate the two (or more) datasets are based on the assumption that only the common variables explain the association between Y and Z (D'Orazio, 2017[25]). If this conditional independence assumption does not hold, the joint dataset will result in incorrect inferences. External auxiliary information can be used to ensure that results derived from statistical matching are reliable (D'Orazio, Di Zio and Scanu, 2006[23]; Leulescu and Agafitei, 2013[26]).

The method of Rubin (1986[24]) relaxes the conditional independence assumption, by taking into account a non-zero partial correlation between Y and Z given a set of control variables X. The statistical matching between PIAAC and CSIS was thus performed in three phases:

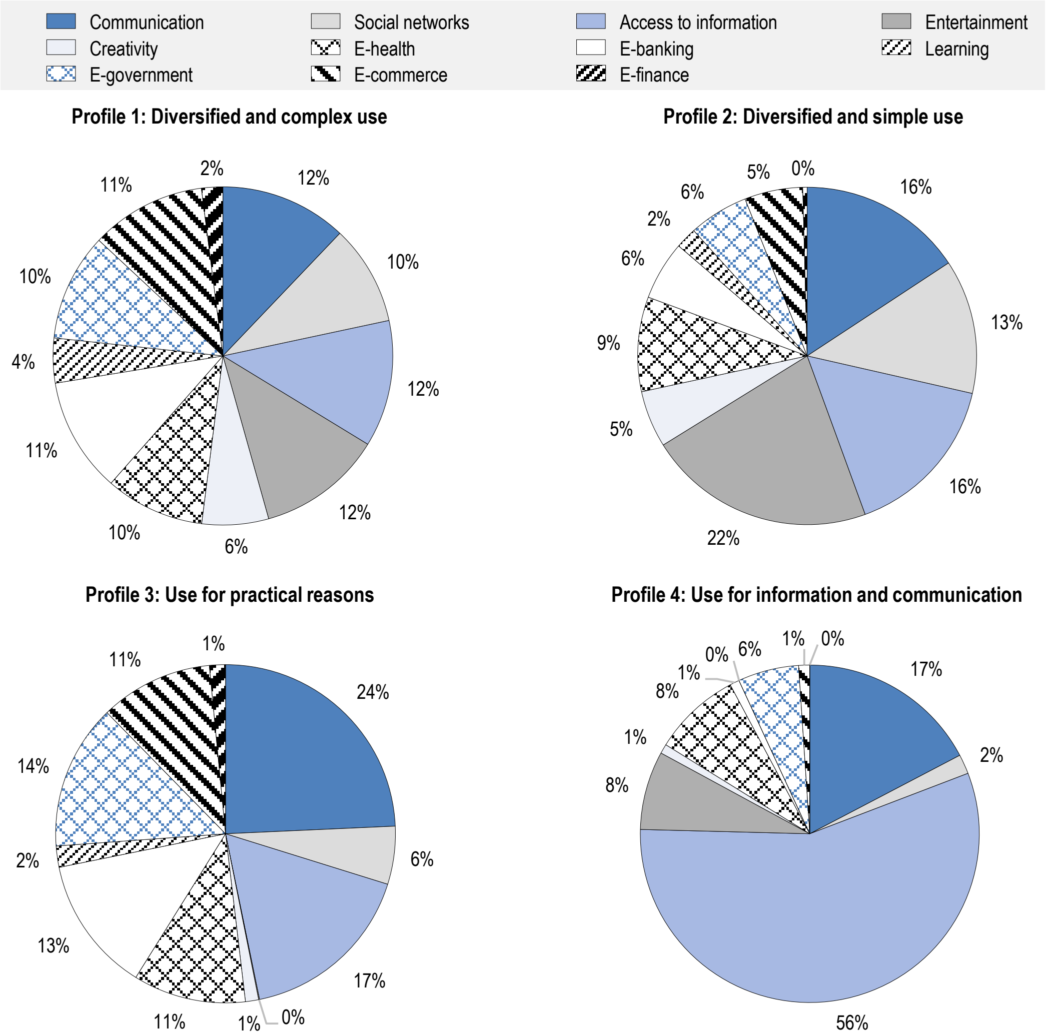
1. The method of Rubin (1986[24]), as implemented by Alpman (2016[27]) was applied to impute the variables on ICT usage for which the value of partial correlation with skills can be derived from auxiliary information available in the Survey of Adult Skills (PIAAC).
2. Missing values of the other variables were imputed with values from a "similar" responding unit (i.e. a random hot deck method), based on the common PIAAC-CSIS variables and on the variables matched through the method of Rubin (1986[24]).
3. Quality checks are performed for both matches (method of Rubin (1986[24]) and random hot deck).

The matching was performed by country, for seven countries (Czech Republic, Finland, France, Ireland, Italy, Lithuania and Spain) out of the 19 that are covered by both the PIAAC and CSIS databases. Data for the Survey of Adult Skills (PIAAC) refers to 2012 (Czech Republic, Finland, France, Ireland, Italy and Spain) and 2015 (Lithuania). CSIS data refers to 2016 in order to capture the most recent and diversified set of ICT-related uses. The skills set of the population is unlikely to have substantially evolved between 2012 and 2016, so the difference in the reference period of the two surveys is not considered as problematic for the subsequent analysis.

Sources: Alpman, A. (2016[27]), "Implementing Rubin's alternative multiple-imputation method for statistical matching in Stata", www.stata-journal.com/article.html?article=st0452 (accessed 2 October 2018); D'Orazio , M., M. Di Zio and M. Scanu (2006[23]), *Statistical Matching: Theory and Practice*, www.wiley.com/en-us/Statistical+Matching%3A+Theory+and+Practice-p-9780470023532 (accessed 3 October 2018); D'Orazio, M. (2017[25]), "Statistical matching and imputation of survey data with StatMatch", www.essnet-portal.eu/di/data-integration (accessed 4 October 2018); Leulescu, A. and M. Agafitei (2013[26]), *Statistical Matching: A Model-based Approach for Data Integration*, http://dx.doi.org/10.2785/44822; Rubin, D. (1986[24]), "Statistical matching using file concatenation with adjusted weights and multiple imputations", http://dx.doi.org/10.2307/1391390.

Figure 4.9. Profiles of online users

Share of each online activity among the activities performed by each profile of users



Note: The analysis was performed on the matched PIAAC-CSIS file including seven countries (Czech Republic, Finland, France, Ireland, Italy, Lithuania and Spain). The identification of profiles is explained in Box 4.3. In the Survey of Adult Skills (PIAAC): Lithuania- year of reference 2015; all other countries- year of reference 2012.

Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis; Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

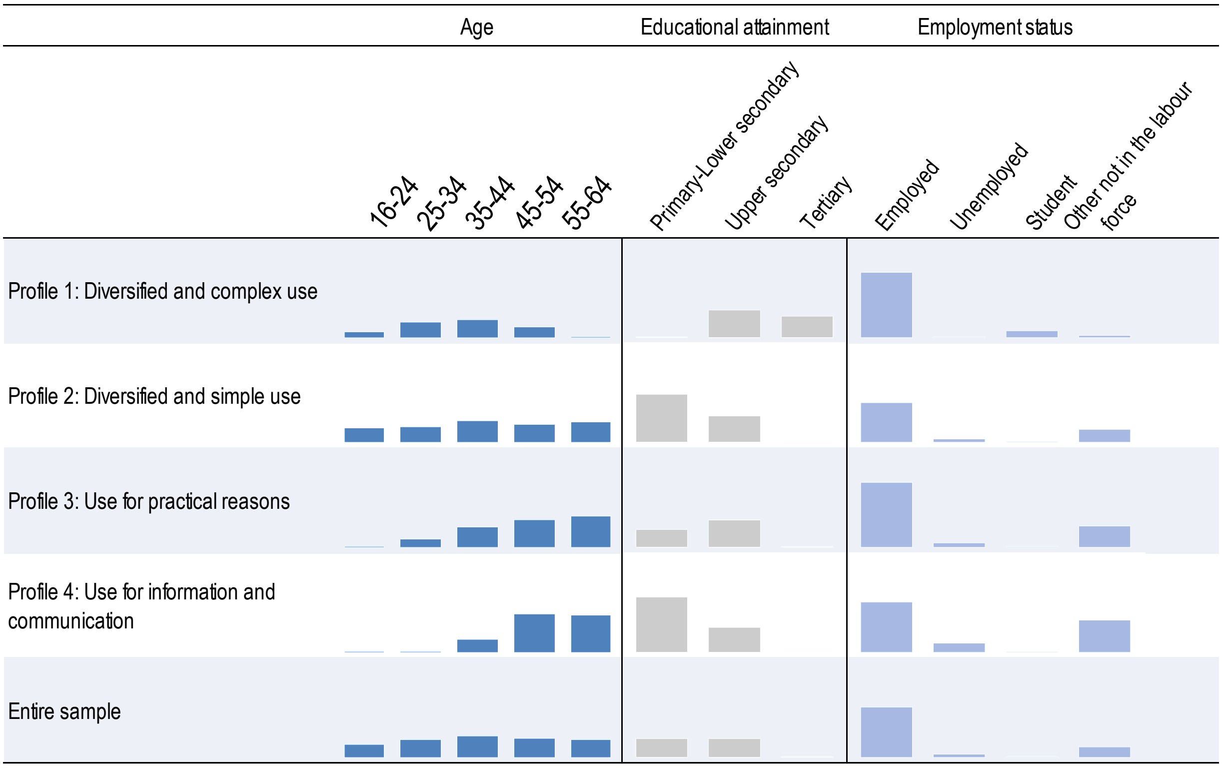
StatLink https://doi.org/10.1787/888933973931

At the opposite end stands Profile 4, “Use for information and communication”, which gathers a majority of those with primary or lower secondary education, aged over 45, either employed or out of the labour force. People in this profile perform few activities and few types of activities. Older individuals are also highly represented in Profile 3, “Use for practical reasons”. This profile gathers not only simple uses such as access to information or communication, but also e-health or e-commerce, which explains the more balanced distribution of educational attainment among users in this profile. Finally, those with diverse but simple uses of Internet (Profile 2) are more likely to be primary-secondary educated and one in four of them is out of the labour force.

These first descriptive statistics offer some hints about where digital inequalities in the use of the Internet may originate. Age, educational attainment and employment status seem to shape both the number and the types of activities that people carry out on line.

Figure 4.10. Profiles of online users and socio-demographic characteristics

Share of individuals in each age/educational attainment/employment status category, by online user profile



Note: The bars display the share of individuals in each socio-demographic category. The maximum value of each share is 100%. The analysis was performed on the matched PIAAC-CSIS file including seven countries (Czech Republic, Finland, France, Ireland, Italy, Lithuania and Spain). The identification of profiles is explained in Box 4.3. In the Survey of Adult Skills (PIAAC): Lithuania- year of reference 2015; all other countries- year of reference 2012.

Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis; Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

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Box 4.3. Identifying profiles of activities performed online through a clustering analysis

The European Community Survey on ICT Usage in Households and by Individuals (CSIS) provides information on what people do on line that can be grouped into 11 major activities: communication, social networks, access to information, entertainment, creativity, learning, e-health, e-banking, e-finance, e-government, and e-commerce.

Each of these 11 activities is defined as a binary variable that takes the value of 1 if individuals perform at least one of the underlying uses associated with that activity (e.g. listening to music on line and watching Internet-streamed TV are both associated with online entertainment). Underlying variables related to Internet use are grouped into types of activities based on a normative approach and on the structure of the CSIS (2016) questionnaire. Twenty-six underlying variables are used for this analysis.

To identify profiles of online users, a clustering procedure was used: individuals were grouped according to the similarity of their online activities.

A *k*-means clustering algorithm (Hartigan, 1975[31]) was used on the matched PIAAC-CSIS file of the seven countries considered in the analysis (Czech Republic, Finland, France, Ireland, Italy, Lithuania and Spain). The initial *k* number of groups was determined by the user. The algorithm departed from a random split of all observations into *k* clusters, then reassigned individuals seeking to minimise within-cluster variance (OECD/JRC-European Commission, 2008[32]).

To detect the clustering with the optimal number of groups, the algorithm was run several times with different values of *k*. The different results were compared using a scree plot (Makles, 2012[33]), showing the change in within-cluster sum of squares as the *k* number of clusters varies. On this basis, four different profiles of online users were chosen for the analysis.

Based on the 11 major online activities defined above, the clustering algorithm measured similarities between individuals using the following clustering variables:

- The share of each activity in the total number of activities performed by an individual online. For example, if one individual performs e-banking, communication, e-government and e-health, then the share of each activity for this individual will be ¼.
- The total number of activities performed by an individual online. In the sample example as above, the total number is 4.

This method allows profiles of online users to be created that account for both the number and types of activities they perform.[1]

Sources: Hartigan, J. (1975[31]), *Clustering Algorithms*, https://people.inf.elte.hu/fekete/algoritmusok_msc/klaszterezes/John%20A.%20Hartigan-Clustering%20Algorithms-John%20Wiley%20&%20Sons%20(1975).pdf (accessed 25 October 2018); Makles, A. (2012[33]), "Stata tip 110: How to get the optimal k-means cluster solution", www.stata-press.com/data/r12/physed (accessed 25 October 2018); OECD/JRC-European Commission (2008[32]), *Handbook on Constructing Composite Indicators: Methodology and User Guide*, www.oecd.org/fr/els/soc/handbookonconstructingcompositeindicatorsmethodologyanduserguide.htm (accessed 25 October 2018).

Skills and Internet profiles

The analysis investigated whether belonging to a given Internet profile is linked to one skill in particular or to a mix of skills. In a first step, as for characteristics listed in the previous section, some descriptive statistics are given on the skills of individuals within each profile.

Around 40% of people with a "diversified and complex use" of the Internet also have a well-rounded literacy and numeracy skills set (Figure 4.11). The share of highly skilled individuals is substantially lower in the other profiles. Among those who use the Internet mainly for information and communication, less than 10% have a well-rounded set of skills.

The share of those lacking basic skills is more evenly distributed across the different profiles. Few people going on line seem to lack both basic literacy and numeracy skills. However, looking at skills separately provides a different picture, especially when numeracy skills are considered. More than 9% of people in Profiles 2, 3 and 4 lack basic numeracy skills, suggesting that a lack of basic numeracy skills is not a barrier to participation in Internet activities, while lacking both literacy and numeracy does seem to be a barrier.

Using a more restricted sample of individuals for whom data on problem solving in technology-rich environments are available, the skills mix of individuals can be defined as including literacy, numeracy and problem-solving skills in technology-rich environments. Individuals with a well-rounded skills set are over-represented in the "diversified and complex use" profile, though fewer individuals are proficient in all three skills (34%) than those who are proficient in literacy and numeracy only (40%). In general, many more people seem to lack problem-solving skills in technology-rich environments. Even among those whose use of the Internet is "diversified and complex", almost one in five lacks basic skills when it comes to solving problems in a digital environment.

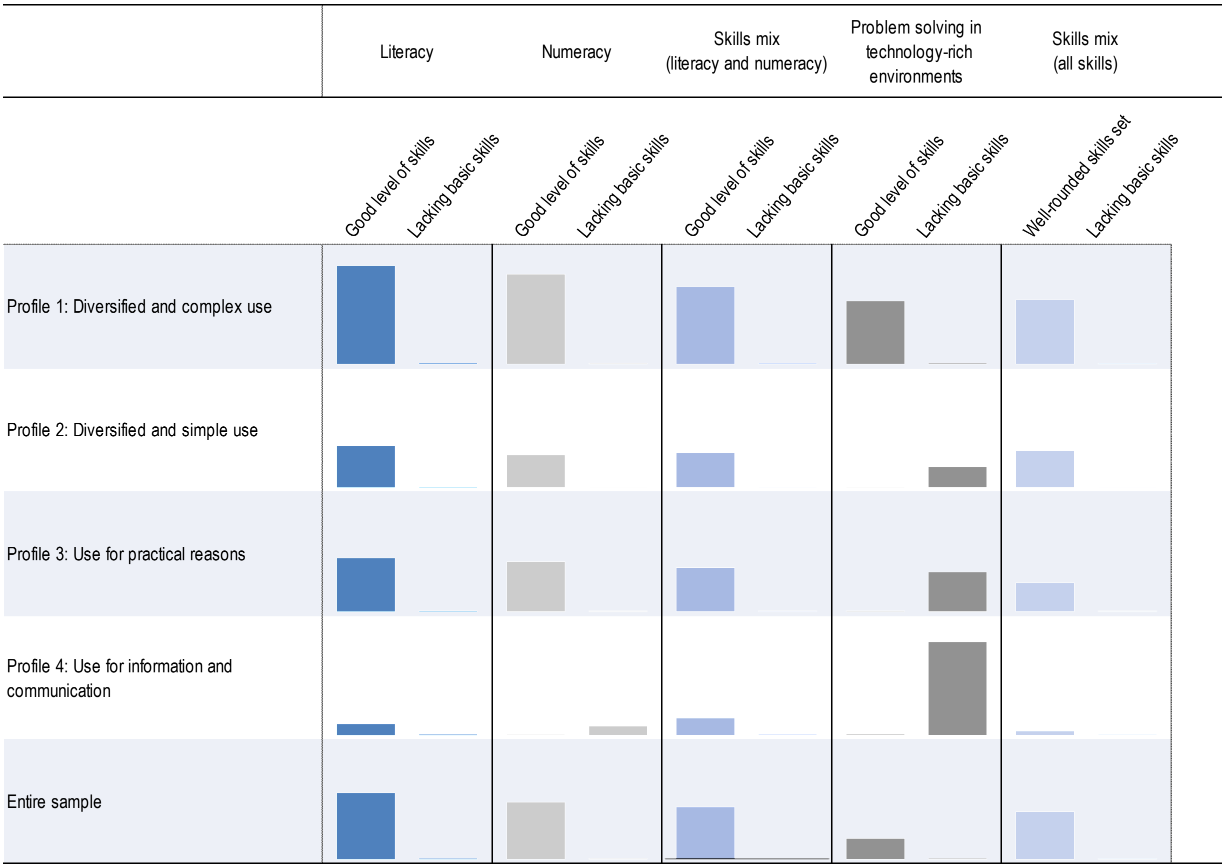
These results suggest that lacking problem-solving skills in technology-rich environment might not be a barrier to participation in online activities, while lacking a mix of skills may be a strong barrier. The problem-solving skills assessed in the OECD Survey of Adult Skills (PIAAC) are not digital skills per se, but basic computer literacy skills (i.e. the capacity to use ICT tools and applications) (OECD, 2016[34]). As such, the assessment cannot capture how prepared an individual is to react to junk email, for instance, or illegal requests for personal information on line. Further data would be needed to uncover any advantage that more advanced digital skills confer compared with the other types of skills used in the analysis.

Having a good level of cognitive skills seems to enable more diverse and complex Internet uses. These descriptive statistics on the skills levels of various Internet user profiles are confirmed by an analysis that accounts for other sources of inequalities and differences in Internet use. Figure 4.10 showed that age, educational attainment and employment status seem to determine the number and types of activities that people carry out on line. Results in Figure 4.12 account for these socio-demographic characteristics, as well as for gender and country effects. People with a good level of skills are more likely to make diverse and complex uses of the Internet, rather than simply go on line for information and communication.

While the analysis shows that one needs an overall good level of skills to move to a more complex and diverse use of Internet, it does not uncover any effect of skills on the likelihood of belonging to the other Internet user profiles ("diversified and simple use" or "use for practical reasons"). This is because other digital divides have a higher influence on the likelihood that individuals belong to one of the two other Internet user profiles.

Figure 4.11. Skills of Internet users by profile

Share of individuals in each skill level category, by online user profile



Note: The bars display the share of individuals in each socio-demographic category. The maximum value of each share is 60%. For literacy and numeracy: individuals lacking basic skills score at most *Level 1* (inclusive); individuals with a good level of skills score at least *Level 3*. For skills mix (literacy and numeracy): individuals lacking basic skills score at most *Level 1* (inclusive) in literacy and numeracy; individuals with a good level of skills score at least *Level 3* in literacy and numeracy. For problem solving in technology-rich environments: individuals lacking basic skills score at most *Below Level 1* (inclusive) in problem solving (including failing ICT core and having no computer experience); individuals with a good level of skills score at least *Level 2* (inclusive) in problem solving. For the skills mix (all skills): individuals lacking basic skills score at most *Level 1* (inclusive) in literacy and numeracy and at most *Below Level 1* (inclusive) in problem solving (including failing ICT core and having no computer experience); individuals with a well-rounded skill set score at least *Level 3* (inclusive) in literacy and numeracy and at least *Level 2* (inclusive) in problem solving.

The analysis was performed on the matched PIAAC-CSIS file including seven countries (Czech Republic, Finland, France, Ireland, Italy, Lithuania and Spain). The identification of profiles is explained in Box 4.3. The sample for the analysis on the effect of good problem-solving skills includes individuals from the Czech Republic, Finland, Ireland and Lithuania. France, Italy and Spain did not participate in the problem-solving skills in technology-rich environments assessment.

In the Survey of Adult Skills (PIAAC): Lithuania- year of reference 2015; all other countries- year of reference 2012.

Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis; Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

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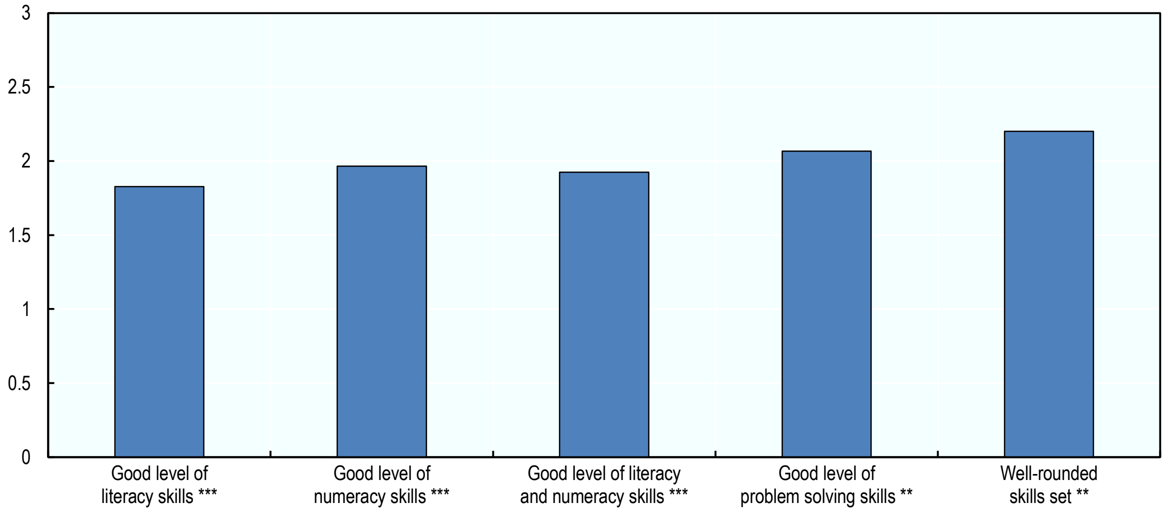
Skills are a prerequisite for fully taking advantage of all the opportunities offered by the digital society. Analyses based on PISA (2015) provided a similar picture: students' performance in paper-based and digital tests are highly correlated and once divides in access are accounted for, differences in the use of digital devices between socio-economic groups are largely due to differences in cognitive skills (OECD, 2015[35]).

Not everyone needs to carry out complex and diverse Internet tasks, but people should be able to do so if wanted, so they need to be empowered with good cognitive skills. Just as the use of emails or social networks appeared innovative and advanced a decade ago, the use of e-finance or the creation of websites are likely to become common practice in a few years – and many other new Internet or technology uses will emerge. The type of skills mix people need to make the most of these new activities could be further refined with detailed data on digital skills as well as on social and emotional skills.

Figure 4.12. Effects of skills on the likelihood to perform diverse and complex Internet uses

Relative risk ratios (comparison profile – "Diversified and complex use", reference profile – "Use for information and communication")



*** - significant at the 1% level.
** - significant at the 5% level.
Note: Each bar displays the relative risk ratio obtained from a multinomial logit regression in which the dependent variable is the profile of Internet user to which each individual belongs and the independent variable of interest is a dummy equal to 1 if the individual has a given level of skills. Skills levels are defined in the note on Figure 4.11. Other independent variables included in the estimation include: age categories, educational attainment level, employment status, gender, and country dummies. The sample for the analysis on the effect of good problem-solving skills and that of having a well-rounded skills set includes individuals from the Czech Republic, Finland, Ireland and Lithuania. France, Italy and Spain did not participate in the problem-solving skills in technology-rich environments assessment. Relative risk ratios are obtained by an exponential transformation of the estimated coefficients from the multinomial logit. Significance levels have been obtained from the estimated coefficients of the multinomial logit.
In the Survey of Adult Skills (PIAAC): Lithuania- year of reference 2015; all other countries- year of reference 2012.
Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis; Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

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Well-being and risks and in a digital society

Better-skilled individuals are likely to benefit more from the opportunities offered by new technologies and hence experience higher life satisfaction. Having the appropriate level of skills is also crucial to protect oneself and others – including children – against the risks that come with life in a digital society.

Safety and privacy issues

As people spend more time on line, they are increasingly exposed to a variety of risks. A majority of individuals surveyed in European countries considered the Internet to be unsafe and more than two-thirds reported having found some type of illegal content on line (Flash Eurobarometer 469, 2018[36]). In the United States, more than 60% of users reported that a data breach had affected their personal information or sensitive online accounts (Olmstead and Smith, 2017[37]).

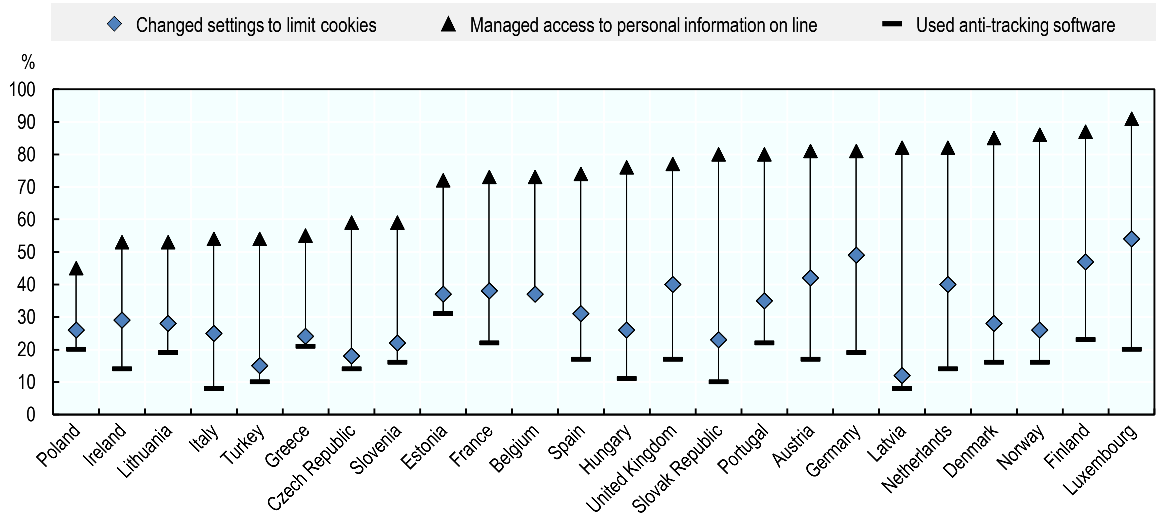
People can do many things to protect their safety on line, from limiting the number of cookies put on their computer to asking websites to delete personal information held about them. Many users know of the threats they face while surfing the Internet, but not all of those conscious of these threats take action to protect themselves. In 2016, in OECD countries with available data, 32% of surveyed individuals were aware that cookies can be used to trace movements of people on the Internet but had never changed the browser settings to prevent or limit them (Eurostat, 2016[30]). There is a large cross-country variation in the share of individuals performing activities related to their security and privacy on line (Figure 4.13). In Poland, Ireland and Lithuania, more than one-third of individuals take no action to manage their personal information on line, in stark contrast with individuals from Luxembourg, Finland or Norway. At the same time, countries with high shares of individuals acting to manage their information on the Internet do not necessarily display similarly high shares of individuals taking steps to avoid their activities being tracked.

These figures suggest that not all online privacy- and security-related actions that individuals can take are equally accessible to all of them. Placing the responsibility of adopting such privacy measures on individuals implicitly assumes that the latter have the necessary skills to do so. Restricting an app's access to the user's geographical location may require just a smartphone click. But checking whether used websites are secure or installing anti-tracking software demands more advanced knowledge and fine understanding of potential threats. Highly skilled individuals are much more likely not only to be aware of such threats but also to take the appropriate steps to ensure safe online navigation.

Analysis based on statistically matched CSIS-PIAAC data shows that having a good level of skills increases the likelihood that individuals take action to protect their privacy and security when they go on line (Figure 4.14). Different sets of skills have different impacts on the type of actions individuals take to ensure their online security and privacy. Managing access to personal information online requires a good level of literacy skills, while using anti-tracking software is more demanding in terms of problem-solving skills in technology-rich environments. Individuals with good literacy, numeracy and problem-solving skills are also more likely to change their website settings to limit cookies. Estimates that account for people's age, education level and country of origin illustrate that individuals endowed with a well-rounded set of skills are more able to protect themselves on line and thus reduce their exposure to a variety of digital risks.

Figure 4.13. Online security and privacy activities

Share of individuals who performed a given activity among those who used Internet within the last year



Note: Individuals who changed settings to limit cookies are individuals who declared changing the settings in their Internet browser to prevent or limit the number of cookies put on their computer. Individuals who managed access to personal information on line are individuals who declared performing any of the following activities: read privacy policy statements before providing personal information, restricted access to their geographical location, limited access to their profile or content on social networking sites, refused to allow the use of personal information for advertising purposes, checked that the website where they needed to provide personal information was secure (e.g. https sites, safety logo or certificate), asked websites or search engines to access the information they hold about them to update or delete it.

Source: OECD calculations based on Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

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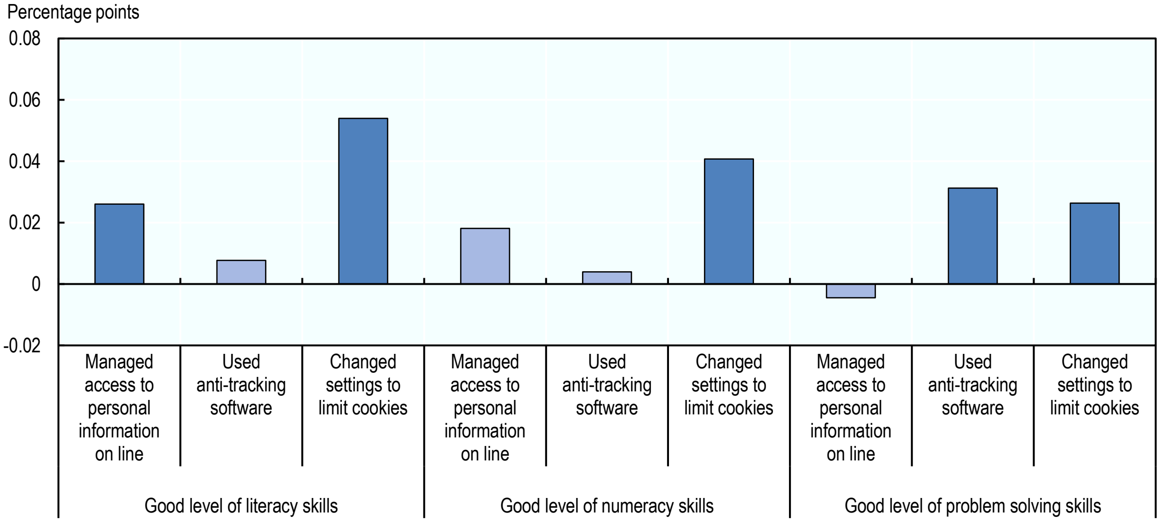
Threats to personal information are not the only risk individuals face online or through new technologies more generally. The spread of "fake news" – online misinformation or disinformation – raises the question of how well individuals, whether children or adults, can critically assess the type of information they encounter on line. In a recent Eurobarometer poll (Flash Eurobarometer 464, 2018[38]), more than one-third of respondents reported encountering "fake news" on a daily basis and another third at least once a week. New technologies facilitate the diffusion of such intentionally misleading or false information, which poses substantial threats not only for trust, political participation and democratic institutions, but also for health or any other outcome for which individuals make decisions based on information found online.

Cyberbullying and other forms of online harassment

The digital environment is also often used to reproduce and amplify harmful behaviour that already exists outside the digital sphere. Cyber-stalking, online harassment and cyberbullying are only a few examples of such behaviours. The Internet provides bullying perpetrators with anonymity and accessibility, reducing fear of punishment and allowing them to be aggressive with the victim at any point in time (Hooft Graafland, 2018[39]). Cyberbullying occurs in many ways, from spreading of false rumours, offensive name-calling and exclusion from online groups, to cyberstalking and even physical threats (Hooft Graafland, 2018[39]; Pew Research Center, 2018[40]).

Figure 4.14. The relationship between skills and online security and privacy activities

Effect of having a given level of skills on performing a given online protection activity



Note: Each bar displays estimated effects of having a given level of skills on the likelihood that an individual performs one of the given activities related to online protection. Other independent variables included in the estimation are: age categories, educational attainment level, employment status, gender, and country dummies. The different activities were defined in the note of Figure 4.13 and are included as dummies in the regression: each dummy is equal to 1 if the individual performed the given activity. Individuals with a good level of literacy (numeracy) skills score at least *Level 3* (inclusive) in literacy (numeracy). Individuals with a good level of problem-solving skills score at least *Level 2* (inclusive) in problem solving. The analysis is performed on the matched PIAAC-CSIS file including seven countries (Czech Republic, Finland, France, Ireland, Italy, Lithuania and Spain). The sample for the analysis on the effect of good problem-solving skills includes individuals from the Czech Republic, Finland, Ireland and Lithuania. France, Italy and Spain did not participate in the problem-solving skills in technology-rich environments assessment.

In the Survey of Adult Skills (PIAAC): Lithuania- year of reference 2015; all other countries- year of reference 2012.

Statistically significant coefficients are displayed in the darker shade.

Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

StatLink https://doi.org/10.1787/888933974026

As with information on other forms of harassment, data on cyberbullying are sensitive to gather. Evidence from the Health Behaviour in School-aged Children survey indicated that on average 9% of children aged 15 in OECD countries with available data had been cyberbullied by messages at least once (OECD, 2019[10]). More recent data from a survey on 750 teenagers in the United States show that 59% had experienced cyberbullying and 63% saw online harassment as a major problem (Pew Research Center, 2018[40]). These contrasting figures suggest that the prevalence of cyberbullying is still hard to measure, even if cyberbullying has been shown to reduce victims’ life satisfaction and harm their mental health (Ybarra and Mitchell, 2004[41]; OECD, 2017[1]; Hooft Graafland, 2018[39]).

Fighting cyberbullying often requires a co-ordinated response from parents, schools, social media and tech companies, as well as lawmakers. Surveyed teenagers in the United States seemed to especially value parents’ efforts to counter online harassment (Pew Research Center, 2018[40]). Teachers, social media sites and even law enforcement were perceived much less favourably. Parents appear to be crucial in tackling cyberbullying. As children start using the Internet at an ever younger age, the scope increases for parents to educate children to use technology and support them when they face risks (Hooft Graafland, 2018[39]).

Parents' digital skills and awareness affect in turn the types of opportunities and threats their children experience online. Digitally skilled parents are more likely to have an enabling approach to Internet use, encouraging their children to explore and learn things on line, sharing online activities with their children, but also explaining why some websites may be inappropriate (Livingstone et al., 2017[42]). While such a strategy may also expose children to more risks, it also enables children to develop resilience and be better prepared to grapple with new risks when they face them. Policies that seek to minimise digital inequalities as well as the risks faced by children and adults online should also aim to boost parents' and children's digital skills, and use levers for skills development.

Mental health and social relationships

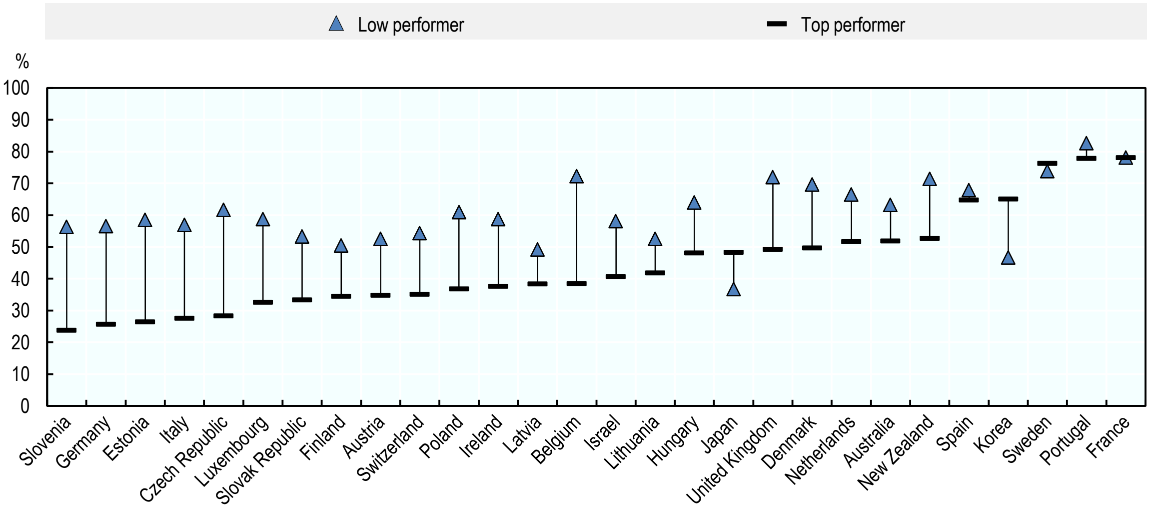
The increasing use of new technologies and devices has triggered fears that they may harm well-being in other ways, including users' mental health and social relationships. Extreme screen-time may reduce sleep quality, increasing the risk of depression and anxiety (Hooft Graafland, 2018[39]). Constant connectivity, especially when it is work-related, may lead to higher levels of stress and emotional exhaustion (Belkin, Becker and Conroy, 2016[43]). The use of new technologies is often associated with multitasking, whereby individuals access several streams of information or media content at the same time. Individuals who multitask using digital devices are more likely to get distracted easily, to have lower efficiency and to experience higher levels of social anxiety (Ophir, Nass and Wagner, 2009[44]; OECD, 2012[45]; Becker, Alzahabi and Hopwood, 2013[46]).

Evidence that the Internet and digital technologies impair mental health has nevertheless proven challenging to establish (Box 4.4). Moderate use of digital technologies mostly seems to have beneficial effects on mental well-being, with no or excessive use having small negative consequences. In OECD countries participating in PISA, extreme Internet users – students who use the Internet more than six hours a day – displayed lower life satisfaction, higher risk of disengagement from school and higher levels of perceived loneliness at school (OECD, 2017[1]). Extreme Internet users also scored less in all PISA subjects, even after taking into account differences in socio-economic background.

Highly skilled individuals are likely to be more informed about the risks associated with extreme uses of technology, and to pay more attention to how much time they spend in front of the computer and how they use devices. Data from PISA suggest that top-performing students are less likely to feel bad without an Internet connection. On average across OECD countries with available data, 45% of students with top performance in reading, mathematics and science reported feeling bad in the absence of an Internet connection, in contrast to 62% among low performers (Figure 4.15).

Figure 4.15. Feeling bad without Internet connection, by students' performance

Percentage of students who reported to agree or strongly agree to feel bad without Internet connection



Note: Students who are low performers are students who score at less than Level 2 in the reading, mathematics and science assessments. Level 2 is considered to be the baseline level of proficiency in reading, mathematics and science. Students who are top performers are students who are proficient at Level 5 or 6 in reading, mathematics and science. Shares for countries with less than 100 observations available for top or low performer categories are not reported in the figure.

Source: OECD calculations based on OECD (2015[22]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

StatLink https://doi.org/10.1787/888933974045

Box 4.4. Digital technologies and mental well-being

On average across OECD countries, 91% of 15-year-olds have access to an Internet-enabled smartphone at home, and 55% to a tablet (OECD, 2017[1]). There is growing worry that digital technologies are having a detrimental impact on people's social interactions and mental well-being, especially for young children and adolescents.

The most robust studies suggest the relationship between Internet/social media use and mental well-being is U-shaped for children and adolescents, with no and excessive use being associated with small negative consequences (Kardefelt-Winther, 2017[47]; Przybylski and Weinstein, 2017[48]). The positive and negative outcomes depend largely on the type of activity and content to which children are exposed. More analysis is needed to establish causality and to obtain a more detailed understanding of the effects of different media contents and uses (Odgers, 2018[49]).

One of the most comprehensive studies to date examined 120 000 15-year-olds in England in 2017 (Przybylski and Weinstein, 2017[48]). Its results suggested no relationship between mental well-being and moderate computer and smartphone use, and very small negative correlations for people who had very low and very high levels of engagement (e.g. over two hours of smartphone use per day). However, these negative impacts were negligible relative to other factors that influence child well-being, such as eating breakfast regularly or getting regular sleep. Another study of 6 000 US children aged 12 to 18 found a small relationship between excessive TV and video game screen time (over six hours per day) and feelings of depression (Ferguson, 2017[50]).

One study attempted to identify the causal impact of social media on 10- to 15-year-olds' mental well-being by exploiting variations in broadband speeds and mobile phone signal strength within the United Kingdom (Mcdool et al., 2016[51]). An increase in time spent on social networks was found to lower children's feeling of satisfaction with all aspects of their lives, with the exception of their friendships. The effect was stronger for girls than for boys. Another experimental study found that passive Facebook use (e.g. simply scrolling through one's newsfeed, viewing others' posts without interacting) induced feelings of envy and lowered participants' affective well-being ("How do you feel right now?") (Verduyn et al., 2015[52]).

Digital communication can improve the well-being and social interactions of elderly adults. Loneliness in old age is an epidemic in many countries. Recent qualitative studies suggest digital technologies, and in particular tablets with communication apps (e.g. Skype, Facetime and Facebook) could help improve seniors' well-being. One study consisting of semi-structured interviews with 21 older adults in an independent living community in the United States found that using tablets made them feel more connected to their families, friends and to the world more generally (Tsai et al., 2015[53]). In another qualitative study, 19 residents of a retirement community were provided with tablets and bi-weekly training (Delello and McWhorter, 2017[54]). Participants found the tablets allowed them to stay connected with their families as well as with friends within and outside the community, with 22% using videoconferencing weekly.

Sources: Delello, J. and R. McWhorter (2017[54]), "Reducing the digital divide: Connecting older adults to iPad technology", http://dx.doi.org/10.1177/0733464815589985; Ferguson, C.J. (2017[50]), "Everything in moderation: Moderate use of screens unassociated with child behavior problems", http://dx.doi.org/10.1007/s11126-016-9486-3; Kardefelt-Winther, D. (2017[47]), "How does the time children spend using technology impact their mental well-being, social relationships and physical activity?", www.unicef-irc.org/publications/pdf/Children-digital-technology-wellbeing.pdf; Mcdool, E. et al. (2016[51]), "Social media use and children's wellbeing", http://ftp.iza.org/dp10412.pdf; Przybylski, A. and N. Weinstein (2017[48]), "A large-scale test of the Goldilocks Hypothesis", http://dx.doi.org/10.1177/0956797616678438; OECD (2017[1]), *PISA 2015 Results (Volume III): Students' Well-Being*, https://dx.doi.org/10.1787/9789264273856-en; Tsai, H. et al. (2015[53]), "Getting grandma online: Are tablets the answer for increasing digital inclusion for older adults in the U.S.?", http://dx.doi.org/10.1080/03601277.2015.1048165; Verduyn, P. et al. (2015[52]), "Passive Facebook usage undermines affective well-being: Experimental and longitudinal evidence", http://dx.doi.org/10.1037/xge0000057.

As new technologies permeate every aspect of society, they change the types of interactions people have not only with their own social networks but also with people they do not know.

Participation in online activities and social networks may complement people's existing offline interactions and thus strengthen their social relations. While evidence on a causal impact of technology use on personal social connections may not yet be conclusive, many studies suggest that the use of digital technologies most likely stimulates existing social relationships (Box 4.5). On the other hand, the increasing digitalisation of societies may be reducing people's face-to-face interactions with strangers and their sense of community.

Box 4.5. Technology use and social relationships

Interactions with friends

There are four main hypotheses regarding how the use of digital technologies may affect offline social interactions (Lee, 2009[55]). (i) The *displacement hypothesis* postulates that online social ties substitute for offline interactions. (ii) The *increase hypothesis* claims that the Internet complements face-to-face relationships. (iii) The *rich-get-richer hypothesis* suggests that people with stronger offline social networks and social skills benefit more from digital technologies in terms of social capital. (iv) The *social compensation hypothesis* proposes that socially anxious and isolated people benefit more from digital technologies, as they are able to communicate more easily online. Some recent studies, summarised below, support the *increase hypothesis*.

The most recent empirical evidence, overall, suggests digital technologies are used by children and adults to develop and maintain social interactions (Kardefelt-Winther, 2017[47]; Yau and Reich, 2018[56]; Odgers, 2018[49]). Current digital technologies facilitate the maintenance of existing relationships, through communication tools (e.g. WhatsApp, Messenger, WeChat) and social networking sites (e.g. Facebook, Instagram, Snapchat). The causal evidence is scarce, however, and most studies evaluate time spent using digital technologies rather than the activities children undertake and the content they interact with, which are likely to play an important role.

A recent randomised control trial in California freely provided computers to low-income students aged 11 to 16 who did not previously have a computer at home (Fairlie and Kalil, 2017[57]). Comparing these children's social participation outcomes with those of children in the control group, who also did not have a computer before the experiment, they found "a significant and positive treatment impact on the number of friends children report communicating with and the amount of time children report actually hanging out with their friends (in person)." Moreover, treated students with no prior participation in social networking or texting experienced greater social connection gains.

Another study exploited a quasi-experiment in eastern Germany stemming from a misguided technological choice by the state-owned telecommunication provider in the 1990s, which hampered the provision of broadband Internet for numerous households (Bauernschuster, Falck and Woessmann, 2014[58]). Exploiting this mistaken technological choice to identify the effect of Internet adoption, they found no evidence that having broadband Internet at home had a negative impact on offline social connections such as going to the movies, concerts, visiting neighbours, friends, and volunteering activities. Their results for children aged 7 to 16 also show no evidence that broadband Internet access crowds out social activities in or out of school, but rather indicates that it may support participation in social group activities outside school.

Interactions with strangers

Smartphones and online services may be eroding a sense of belonging and community by eliminating opportunities for short casual interactions with strangers. Such interactions are important for trust building and facilitating the ease of social interactions. For example, while people trying to find their way in a city used to ask around for help and directions, they now look up their location on their smartphone's map app. Short encounters would take place while commuting or in queues. Now, many people in such situations stare at their screens to check their social media or watch TV shows. These developments are too recent for a definitive assessment of their likely societal implications, but they should be examined carefully.

Using US data from the World Values Survey, a recent study found that using one's mobile phone more frequently to obtain information was associated with trusting strangers less (Kushlev and Proulx, 2016[59]). The relationship remained after taking into account a number of individuals' characteristics (e.g. income, education, employment status, age). Moreover, obtaining information from other media sources such as TV, radio, and even online but through a laptop computer was not similarly associated with lower trust in strangers. Another study randomly assigned 92 predominantly young adults to look for a building either with or without a phone (Kushlev, Proulx and Dunn, 2017[60]). They found that very few participants in the phone group talked to people to obtain directions and, on average, they felt less socially connected.

Sources: Bauernschuster, S., O. Falck and L. Woessmann (2014[58]), "Surfing alone? The internet and social capital: Evidence from an unforeseeable technological mistake", http://dx.doi.org/10.1016/j.jpubeco.2014.05.007; Fairlie, R. and A. Kalil (2017[57]), "The effects of computers on children's social development and school participation: Evidence from a randomized control experiment", http://dx.doi.org/10.1016/j.econedurev.2017.01.001; Kardefelt-Winther, D. (2017[47]), "How does the time children spend using technology impact their mental well-being, social relationships and physical activity?", www.unicef-irc.org/publications/pdf/Children-digital-technology-wellbeing.pdf; Kushlev, K. and J. Proulx (2016[59]), "The social costs of ubiquitous information: Consuming information on mobile phones is associated with lower trust", http://dx.doi.org/10.1371/journal.pone.0162130; Kushlev, K., J. Proulx and E. Dunn (2017[60]), "Digitally connected, socially disconnected: The effects of relying on technology rather than other people", http://dx.doi.org/10.1016/J.CHB.2017.07.001; Lee, S. (2009[55]), "Online communication and adolescent social ties: Who benefits more from Internet use?", http://dx.doi.org/10.1111/j.1083-6101.2009.01451.x; Odgers, C. (2018[49]), "Smartphones are bad for some teens, not all", http://dx.doi.org/10.1038/d41586-018-02109-8; Yau, J. and S. Reich (2018[56]), "Are the qualities of adolescents' offline friendships present in digital interactions?", http://dx.doi.org/10.1007/s40894-017-0059-y

Being connected and skills development

Technology itself may affect the development of skills. People rely increasingly on the Internet, smartphones or computers for even the simplest tasks. For many, looking for directions has become a task for a smartphone rather than requiring thinking or interaction with surrounding people. Evidence is emerging that technology use affects memory and cognitive development. When people are confronted with difficult questions, they are primed to rely on computers. When they expect to be able to access information online, they are less likely to be able to recall that information (Sparrow, Liu and Wegner, 2011[61]). People appear to be outsourcing not only their memory or information storage to digital devices, but also their thinking (Barr et al., 2015[62]).

Technology may also affect the development of social and emotional skills, but there is still too little evidence to draw conclusions about this link (Box 4.6). Social and emotional skills are increasingly valued in a digital world, but the acquisition of such skills is likely to be hindered if people interact more frequently with computers and technology lowers the quality of social interactions.

Box 4.6. Digital technologies and the development of socio-emotional skills

Friendships and face-to-face interactions with peers are vital for the development of life-long social skills, so there are concerns that children's social skills might be impaired if such interactions are replaced by the use of digital technologies (George and Odgers, 2015[63]). Evidence suggests that such technologies tend to stimulate relationships (Box 4.4), but little is known about the extent to which technology use by children might affect their development of social and emotional skills. So far, the limited number of causal studies do not find any effect of computer use at home on children's socio-emotional skills.

Many children in advanced economies use a smartphone with an Internet connexion and are active on multiple social media platforms (George and Odgers, 2015[63]). These have been found to affect the quality of face-to-face interactions, with possible implications for the development of social and emotional skills, but more research is needed to understand the links. One study of 100 pairs found that 10-minute conversations were rated as significantly inferior, with lower levels of empathy, when one participant placed a mobile device on the table or held it in his or her hand, compared with conversations without the presence of a mobile device (Misra et al., 2016[64]).

Increasing psychological evidence suggests parental use of mobile devices adversely affects child-parent interactions. In the United States, 51% of US adolescents (13 to 17 years old) said their parents were "often" (14%) or "sometimes" (34%) distracted by their cell phone when they were trying to have a conversation in person" (Pew Research Center, 2018[65]). Parents who use their smartphones during parent-child play are usually less sensitive and responsive to their children, verbally and non-verbally, and children are more likely to engage in risky behaviours (Kildare and Middlemiss, 2017[66]). More longitudinal studies are needed to assess robustly how these changes in parent-child interactions affect children's long-term socio-emotional skills development, whether the context in which the interaction takes place (e.g. during meals, playtime, vacation) or the type of mobile phone activity undertaken by the parent makes a difference.

A review of 27 studies of parental mobile device use during parent-child interactions found that device use may compromise the development of a secure attachment relationship and child development, (Kildare and Middlemiss, 2017, p. 580[66]). One study of 225 interactions during meals between low-income mothers and their children (around 6 years old) found that mobile use by mothers was associated with 20% fewer verbal and 39% fewer non-verbal interactions and 28% fewer encouragements, compared with no mobile use (Radesky et al., 2015[67]). Mothers' characteristics such as age, ethnicity, education and parenting style were not related to mobile use. Repeated lack of engagement with children may affect their non-cognitive development, as they have fewer opportunities to pick up social cues.

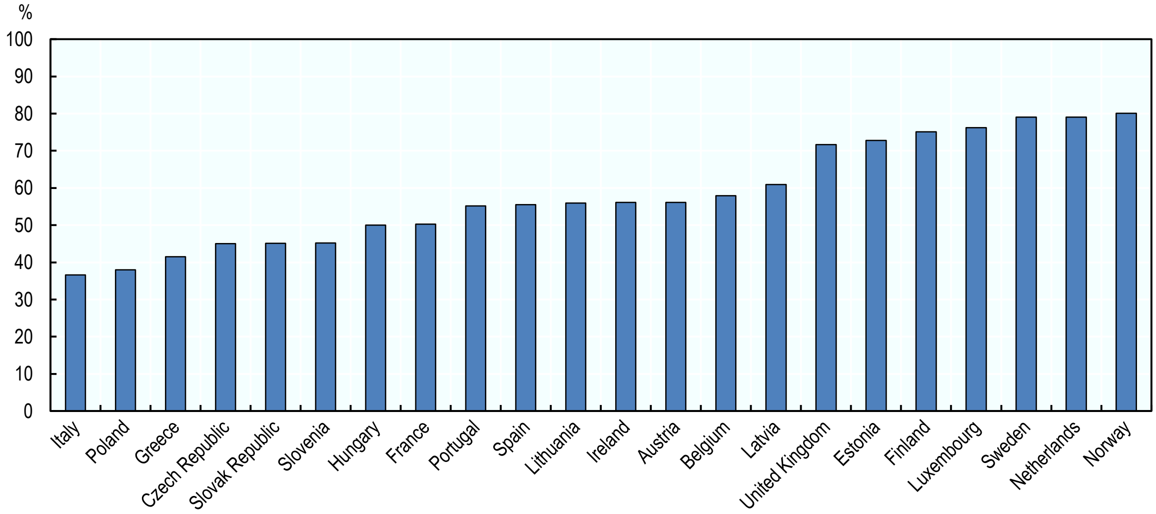
Sources: Fiorini, M. (2010[68]), "The effect of home computer use on children's cognitive and non-cognitive skills", http://dx.doi.org/10.1016/J.ECONEDUREV.2009.06.006; George, M. and C. Odgers (2015[63]), "Seven fears and the science of how mobile technologies may be influencing adolescents in the digital age", http://dx.doi.org/10.1177/1745691615596788; Kildare, C. and W. Middlemiss (2017[66]), "Impact of parents mobile device use on parent-child interaction: A literature review", http://dx.doi.org/10.1016/J.CHB.2017.06.003; Malamud, O. and C. Pop-Eleches (2011[69]), "Home computer use and the development of human capital", http://dx.doi.org/10.1093/qje/qjr008; Misra, S. et al. (2016[64]), "The iPhone effect: The quality of in-person social interactions in the presence of mobile devices", http://dx.doi.org/10.1177/0013916514539755; Pew Research Center (2018[65]), *How Teens and Parents Navigate Screen Time and Device Distractions*, www.pewinternet.org/2018/08/22/how-teens-and-parents-navigate-screen-time-and-device-distractions/; Radesky et al. (2015[67]), "Maternal mobile device use during a structured parent-child interaction task", http://dx.doi.org/10.1016/j.acap.2014.10.001.

Skills-related policies for a digital society

The digitalisation of economies requires people to be well-rounded, or relatively proficient in many cognitive, social and emotional skills, so they can adapt to their changing environments. The ability to learn new things, whether they be tasks or know-how, is also becoming increasingly important in a digital world. Digitalisation increases the variety of tasks executed on the job or activities performed in everyday life, and the use of cognitive skills. Across OECD countries with available data, there is significant variation in the share of individuals using the Internet in diverse and complex ways (Figure 4.16). In the Netherlands, Norway and Sweden, more than 80% of those aged 16 to 64 perform many and complex activities online, including e-finance or the creation of websites and blogs. In contrast, less than half of individuals in Greece, Italy and Poland engage in such activities. These figures suggest that even where Internet access is universal, there are large disparities in the extent to which people from different countries take advantage of all the opportunities brought about by digitalisation. If technological change continues to expand the number and complexity of activities that individuals are required to perform in their everyday life using digital tools, people in some countries are more likely to be left behind.

Figure 4.16. Individuals with a diversified and complex use of Internet

Share of individuals, by country



Note: The identification of the individuals with a diversified and complex use of Internet is based on a clustering methodology similar to that explained in Box 4.3, but applied to the entire sample of OECD countries with available data in the European Community Survey on ICT Usage in Households and by Individuals (2016).

Source: OECD calculations based on Eurostat (2016[30]), *European Community Survey on ICT Usage in Households and by Individuals*.

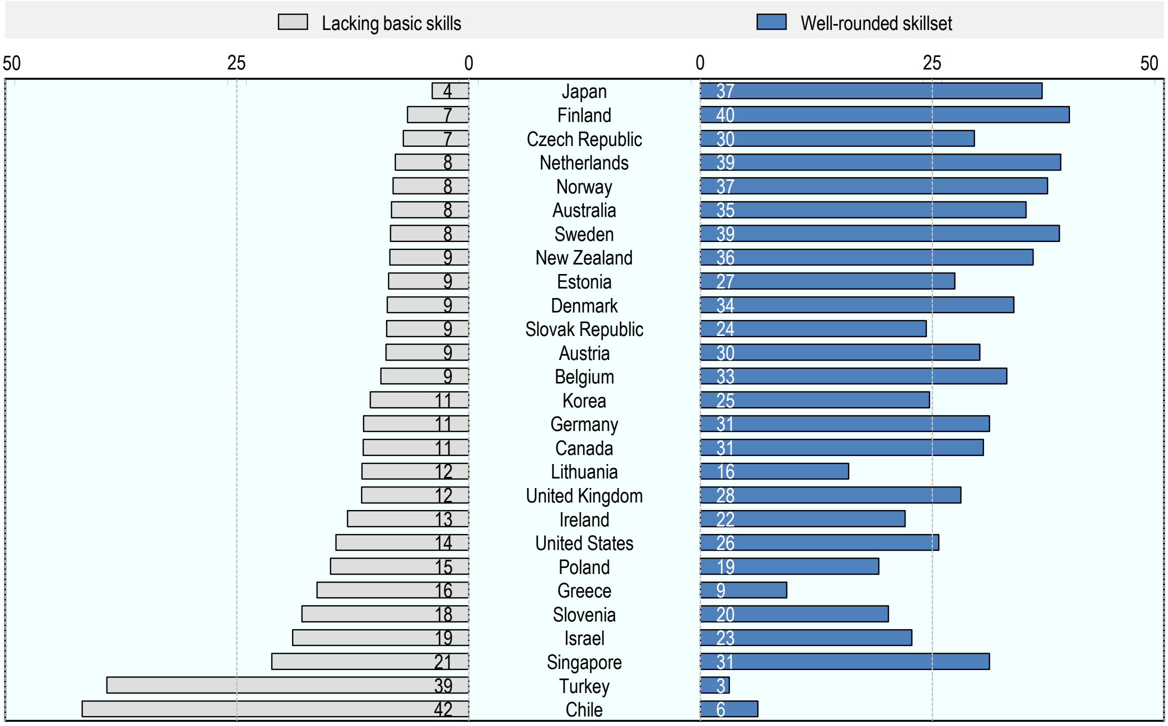
StatLink https://doi.org/10.1787/888933974064

Countries with high proportions of well-rounded individuals and few adults lacking basic skills are likely to be better prepared for technological change than countries where a large share of the population lacks basic skills.

The Survey of Adult Skills (PIAAC) gives an indication of the mix of cognitive skills of countries' populations but does not cover other important types of skills discussed in this chapter, such as social and emotional skills. Finland, the Netherlands, Norway and Sweden, where many people use the Internet in complex and diverse ways, are also among the OECD countries with the highest shares of individuals with well-rounded cognitive skills (Figure 4.17). Countries' population skill mix, which encompasses literacy, numeracy and problem-solving skills in technology-rich environments, varies substantially. As might be expected, countries that perform well in each separate skill, such as Finland, Japan, the Netherlands and Sweden, also tend to have a high proportion of their population with high proficiency in all three skills. These individuals are more likely to be able to adapt if digitalisation affects their job content or everyday activities, since they already have the well-rounded skill mix that is required for learning new working techniques, methods, or technologies.

Figure 4.17. Skills mix of countries' populations

Share of 16-65 year-olds lacking basic skills or having a well-rounded skill set, by country (%)



Note: Individuals lacking basic skills score at most *Level 1* (inclusive) in literacy and numeracy and at most *Below Level 1* (inclusive) in problem solving (including failing ICT core and having no computer experience). Individuals with a well-rounded skill set score at least *Level 3* (inclusive) in literacy and numeracy and at least *Level 2* (inclusive) in problem solving. Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933974083

Countries with well-rounded populations also tend to have small proportions of adults who lack the required combination of basic cognitive skills including ICT skills and hence are likely to struggle to adapt to the changes of digitalisation. In Singapore and Israel, the proportion of adults lacking these basic skills reaches close to one in five. In Chile and Turkey, the share is twice as high.

People lacking basic cognitive skills are most at risk of not being able to adapt in a digital environment and should thus be a particular focus of policy. The aggregate share of low-skilled adults hides important variations among subgroups. Youth (16-24) are less likely to lack basic skills than prime-age people (25-54) and older people (55-65), with only a minority of young people lacking basic skills (Figure 4.18). In particular, on average, only around 7% of youth have low proficiency in all three skills (literacy, numeracy and problem solving with computers), while 23% of older people do. Prime-age adults fare closer to youth with, on average, 12% lacking basic skills.

There are significant variations between countries, with some having a much more prepared prime-age workforce, such as the Czech Republic, Finland and Japan, while others, notably Chile and Turkey, have significant shares of unprepared adults, pointing to different policy priorities for different countries. In countries with a high share of people lacking basic skills and young people not performing much better than prime-age ones (e.g. Greece and to some extent the United Kingdom), the focus needs to be put on improving the quality and inclusiveness of initial education. In countries where there is a much larger share of older individuals lacking basic skills than of young people (e.g. Korea and Slovenia), the priority needs to be put on policies to ensure that older individuals are not left behind by the digital transformation.

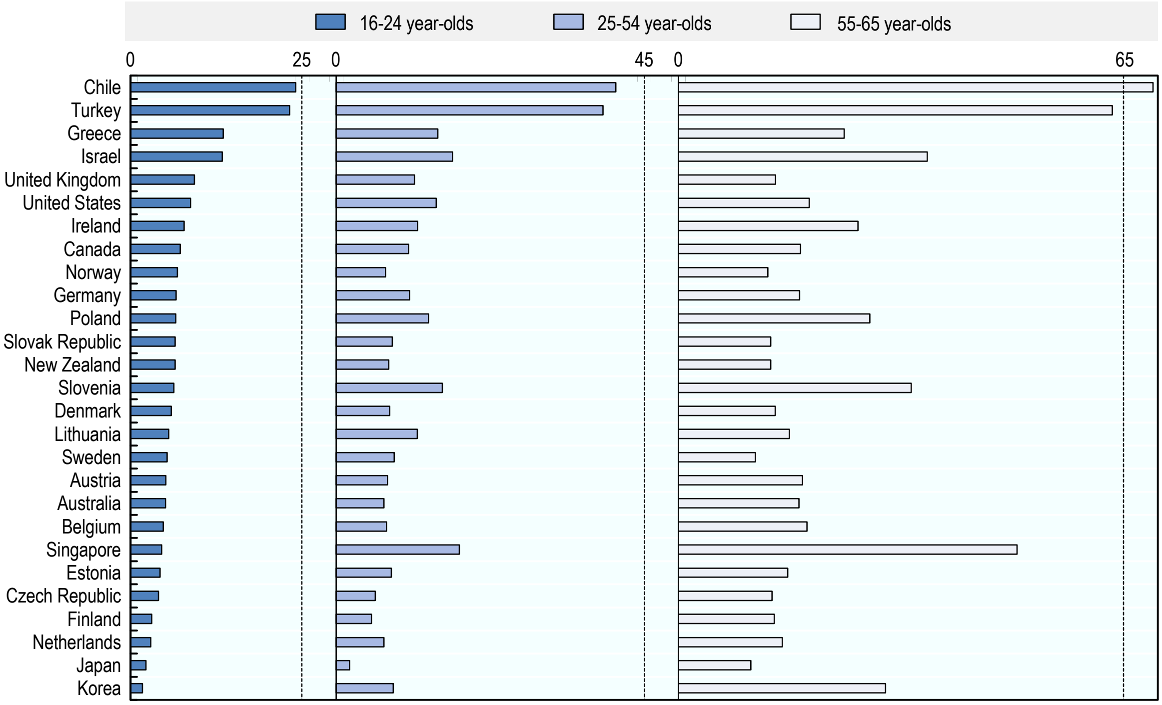
Preparing individuals for a digital society needs to begin early, in families and schools where parents and teachers equip children not only with the necessary cognitive skills but also with digital resilience – the ability to manage the risks and opportunities of going on line (Hooft Graafland, 2018[39]; Hatlevik and Hatlevik, 2018[70]). Parents' involvement in their children's digital education is increasingly important, as many children first access digital devices at home. When parents lack the skills required to help children manage their online activity, others need to step in to build children's digital resilience and avoid further exacerbating digital inequalities.

Teachers and schools are natural candidates to support the development of digital skills and digital resilience. To ensure education systems are able to adapt to new requirements, professional development programmes need to prepare teachers and school to educate students on online safety and privacy, understand the implications of some online behaviours and identify various forms of online harassment that build up in schools. Integrating online safety or digital citizenship responsibilities in the curriculum can also be considered, although more evaluations are needed to establish the effectiveness of such interventions (Hooft Graafland, 2018[39]). Beyond education systems, policy makers could also consider a co-ordinated regulatory response to child protection and better measuring and monitoring of existing policies (OECD, 2018[71]).

Local communities and associations can also help people develop their digital skills and resilience. In Denmark, local libraries offer digitalisation courses (European Commission, 2018[72]). In the United Kingdom, the Future Digital Inclusion programme, funded by the government and run by a charity, has provided support and training to more than 200 000 individuals in basic digital skills (Department of Digital, Culture, Media and Sport, 2017[73]). In a similar vein, the NHS Widening Digital Participation programme, delivered by a charity through networks of local online centres, has trained people to use digital health resources and tools to tackle health inequalities and digital exclusion (Tinder Foundation, 2016[74]). Such initiatives also emphasise the need for programmes and tools that accompany low-skilled individuals or the elderly when public services become digitised.

Figure 4.18. Share of individuals lacking basic skills by age groups

Share of youth (16-24), prime age adults (25-54) and older people (55-65) lacking basic skills, by country (%)



Note: Individuals lacking basic skills score at most *Level 1* (inclusive) in literacy and numeracy and at most *Below Level 1* (inclusive) in problem solving (including failing ICT core and having no computer experience). Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[28]) and OECD (2015[29]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933974102

For all age groups, developing lifelong learning needs to be at the core of the policy answer to the digital transformation (Chapter 6). Digitalisation in itself brings many new learning opportunities in schools, at work and in everyday life.

A high-quality education system, from early childhood education to tertiary education and vocational education and training, can help develop the mix of skills people need to work and live in a digital world, including cognitive and digital skills, social and emotional skills, and a strong readiness to learn. There is a growing consensus about the importance of transversal skills or "21st century skills" such as thinking critically and creatively, solving problems, making informed decisions while using technology, and behaving collaboratively, as evidenced by the analysis in the previous chapters. At the same time, developing these skills cannot come at the expense of content knowledge, as working in a digital environment requires a deep grasp of substance. To achieve these aims, education and training systems have to move to a multidisciplinary approach to knowledge that imparts a range of skills and values, so that people can complete complex thinking and problem solving tasks.

Summary

This chapter aims to better understand the types of skills people need to benefit from new technologies in their everyday life. To do this, it combines information on cognitive skills, from the Survey of Adult Skills, with information on participation in online activities, from the Community Survey on ICT usage in households and by individuals. More data will be needed, however, to obtain a comprehensive view of the whole range of skills that can affect online behaviour, including high-level digital skills and social and emotional skills, and the role for policies.

The analysis proposed in the chapter shows the importance of literacy and numeracy skills as well as problem-solving skills in technology-rich environments to perform diversified and complex activities on line. While not everybody needs to perform these activities, people need to have the relevant skills to be able to choose how they participate in online activities.

Countries differ significantly in how well their populations' skills prepare them for digitalisation. An important question for the design of policies is to assess whether the skills gap between generations tend to decrease or not when a range of skills is considered, including digital ones.

People are not equally equipped to benefit from online opportunities. A range of policies is needed to ensure that the development of new technologies does not lead to inequalities of opportunities between children or between workers, or social isolation for older people. Policies should acknowledge the role of schools and the teaching profession in combatting exposure to risks, and the need for co-operation between local government and communities to bridge gaps in the skills people need to make use of online activities. Policies targeting skills, value and knowledge development need to be accompanied by policies that help people ensure the security and safety of their online activities.

Note

[1] The clustering algorithm is also run on the original variables of the online activities, defined as binary variable that equal 1 if the individual performs a given activity. The algorithm yields similar results to those computed using activity shares and the total number of activities.

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Chapter 5. Learning in a digital environment

This chapter examines the opportunities that technology offers for skills development, in schools, higher education and throughout life. It explores the relationship between technology use in schools and students' performance. It also investigates teachers' use of new technologies and how policies can unlock the potential of technology for teaching and learning. Outside schools, technology offers new sources of lifelong learning through open education and massive open online courses. This chapter shows that inequalities persist in adults' participation in online learning activities and discusses how governments can adapt systems for recognising and certifying skills when sources for learning diversify.

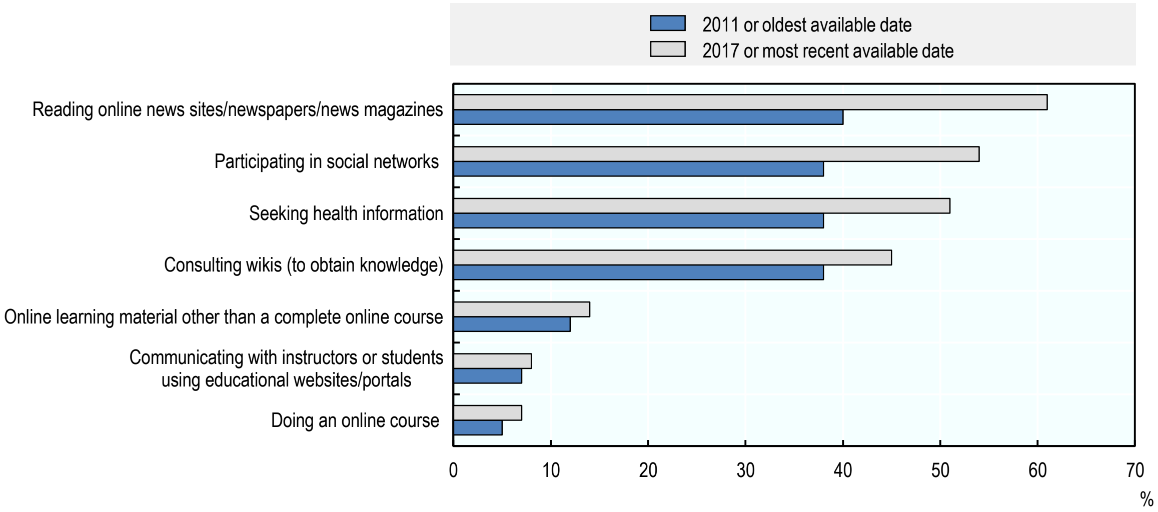
The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

As technology changes, so do the skills people need to thrive in work and life. At the same time, new technologies can enhance learning opportunities and help develop skills for the 21st century. The Internet, videos and applications, have facilitated access to knowledge and have changed the way people learn at home, at work, and in schools. An almost infinite amount of information is available for anybody who browses the Internet. The challenge is learning to select between various sources and make good use of the information they provide.

Open Education Resources, the digital learning resources offered online freely and openly to teachers, educators, students and independent learners, can be used in teaching, learning and research (Orr, Rimini and van Damme, 2015[1]). Beyond Open Education Resources, people learn from networks of those who are debating their ideas online (Weinberger, 2011[2]). They learn from material not specifically designed as educational material. In European countries, more than 50% of individuals read online news, seek health information online or participate in social networks. Close to 50% obtain knowledge from wikis – websites developed collaboratively by communities of users (Figure 5.1).

Figure 5.1. Internet use for activities that can lead to learning

European Union (28 countries), as a percentage of all individuals



Note: Most recent available date is 2015 for “consulting wikis (to obtain knowledge)”. Oldest available date is 2015 for “online learning material other than a complete online course” and “communicating with instructors or students using educational websites/portals”.
Source: Eurostat (2017[3]), *European Community Survey on ICT Usage in Households and by Individuals*.

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These activities can help people develop their knowledge and learn informally across life but they can also distract individuals, such as students, from their main job or learning activities. If teachers are not well prepared, they may simply loose time by using technology in the classroom.

The Internet and smartphones have changed people’s relationship to knowledge by making information available at any time and often, without any cost. But the Internet is also changing the way people remember and solve problems. Those relying on the Internet to access information are more likely to depend on the Internet than on their memory to access other information (Storm, Stone and Benjamin, 2017[4]). The mere presence of smartphones

– for example, when people think about the possibility of using their phones but do not actually use them – can reduce available cognitive capacity (Ward et al., 2017[5]).

As smartphones specifically and technology more generally have entered the workplace, the classroom and everyday life, it is important to understand better how technology changes the way people learn, how it can help develop digital skills and the complementary skills people need, and how policies can make the most of technology for learning.

This chapter discusses how to integrate technology in schools and the extent to which it can provide new opportunities for lifelong learning. It draws from a range of databases, including three maintained by the OECD: the Programme for International Student Assessment (PISA), the Survey of Adult Skills carried out by the Programme for the International Assessment of Adult Competencies (PIAAC) and the Teaching and Learning International Survey (TALIS). The chapter examines how learning and teaching have changed with the development of technology and how policies can help people take advantage of new learning opportunities. Employers need clear signals on a broadening range of skills that workers may have, so it is becoming increasingly crucial to certify skills. As sources of learning diversify, however, this becomes more difficult. The chapter ends by discussing how policies can better recognise and certify skills.

The main findings in this chapter concern three main areas: integrating technology in the classroom, the use of open education and massive open online courses, and the need for better certification.

In schools, mere access to and use of computers is not enough to enhance student performance. The effect of technology on student outcomes depends on how technology is integrated in the classroom and used to support teaching and learning practices:

- Access to ICT infrastructure in schools is extensive in most OECD countries and socio-economically disadvantaged students have similar levels of access as advantaged ones.
- Student use of school computers, laptops or tablets available in schools is not widespread, however, and the share of students using these tools has decreased in many countries. At the same time, the frequency of digital device use at school has increased, driven by the surge of chatting at school, suggesting that students may simply be using their own mobile devices more during school time for no learning purposes.
- Students with very high levels of digital device use at school generally perform less well, whether in mathematics, reading or science. Extensive use of new technologies at school may replace other, more efficient educational practices or simply distract students.
- Many types of frequent digital device use at school tend to be found among student who perform poorly in science, mathematics and reading, even when students' socio-economic status and other characteristics are accounted for. Test scores are higher only for those who browse the Internet for schoolwork regularly. Looking up information may indeed be done more effectively using digital devices.
- The digitalisation of economies and societies increases the need to develop a set of digital skills in school. As student assessments rarely measure digital competencies, there is little evidence on how to best develop these skills. Nevertheless, countries need to make sure they implement a consistent approach throughout the school years, focusing on what needs to be learnt, such as computational thinking, rather than on specific computer use or software skills that can quickly become obsolete.

- Teachers' digital competencies are instrumental for their own students' capacity to make the most out of new technologies. There is a significant positive relationship between teachers' problem-solving skills in technology-rich environments and students' performance in computer problem solving and computer mathematics.
- At the same time, teachers are less likely than other tertiary-educated graduates to be high performers in problem solving in technology-rich environments. Many teachers specifically report needing professional development in ICT skills for teaching. There is a need to provide quality training to teachers on how to best integrate the technology in their pedagogical practices. More generally, governments' focus should move from investing in resources to ensuring a tailored approach to technology use, in which teachers have the necessary ICT support and training to rely on digital tools.

Open education and massive open online courses (MOOCs) offer important new sources for knowledge and skills development across life. At this stage, however, they seem to reinforce rather than reduce inequalities in participation in adult learning and little is known on their outcomes in terms of skills development:

- The increasing uptake of MOOCs on a broad range of topics – including the development of social and emotional skills and the capacity to learn more – suggests that some people are well aware of the need to adjust skills throughout life and take action to do so. However, little is known about the quality of such courses and it is likely that there are large variations among them. More data are needed to better understand how people may learn through MOOCs.
- While open education and MOOCs can generally be accessed for free, patterns of participation seem to reproduce those of standard adult education and training. Highly educated and highly skilled adults are more likely to participate.
- Open education is mostly used by those who combine work and formal education, and, to a lesser extent, those who are employed but not in formal education. Hence it seems to be a promising way to facilitate workers' lifelong learning. Yet the potential that open education and MOOCs can offer to firms to train their workers is not being fulfilled, despite some initiatives in this area.
- Governments can work with education and training providers, employers, job-search agencies and MOOC platforms to: i) develop broader participation in open education; and ii) expand the use of MOOCs on the job. In parallel, there is a need to define standards and good practices to better signal the quality of MOOCs.

Better recognition and signalling of skills acquired throughout life would help employers to recruit the right person and provide people with incentives to continue learning. Technology brings some solutions: online certification of a broad range of skills has been developed. Governments can build on this trend to adapt systems of recognition and certification of skills to changing needs:

- Employers need clear signals about workers' and job-seekers' knowledge and their cognitive, social and emotional skills. That means governments, employers, and education and training institutions need to co-operate to build a competencies-based approach to formal qualification. This would require moving towards a reliable assessment of skills rather than a certification of participation in learning activities.
- Governments can work together to harmonise recognition and certification of skills practices at an international level.

Making the most of technology at school

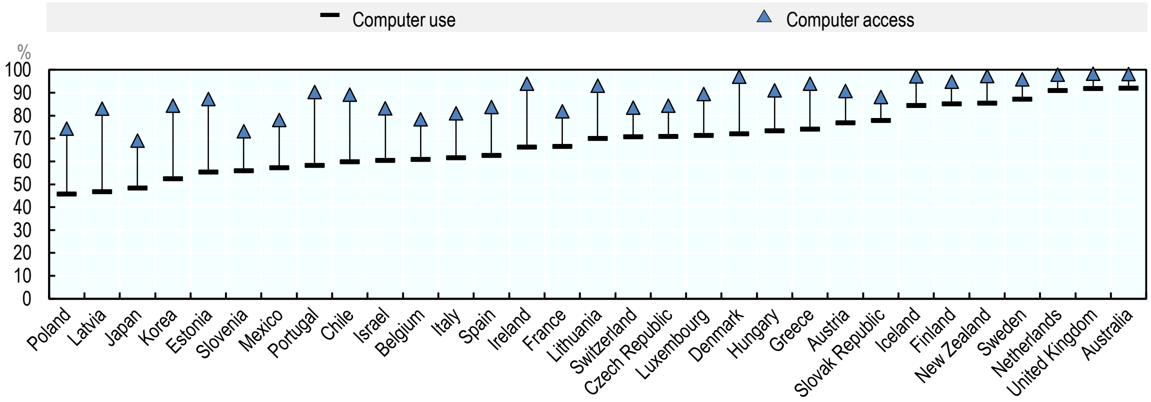
In schools, the use of technology can not only help students develop the skills they need for a digital future but also enable innovative ways of teaching that prevent schools failure. This section investigates the links between technology use in schools and students' outcomes, and the importance of teaching practices in integrating technology in the classroom.

Access and use of digital technologies in schools

Digital tools have been widely introduced in schools. They include computers, tablets, computer-assisted instruction, and games. By 2015, in OECD countries that participated in the Programme for International Student Assessment (PISA), almost 9 in 10 students had access to computers in schools (Figure 5.2). In some countries, however, the use of such devices in schools remains far from widespread. In Poland, less than half of students reported using desktop computers, laptops or tablets that were available for them at school. In Australia, by contrast, almost all 15-year-olds indicated doing so. On average, around two-thirds of students made use of computers at school in the OECD countries that participate in the PISA ICT questionnaire.

Figure 5.2. Access and use of computers in schools

Share of students reporting that a desktop computer, laptop or tablet is available for them at school and share of those who use it, 2015



Note: Students with computer access at school are students for whom a desktop computer, a portable laptop/notebook or a tablet computer is available to use at school, whether they use it or not. Students who use computers at school are students for whom a desktop computer, a portable laptop/notebook or a tablet computer is available to use at school and who use it.

Source: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

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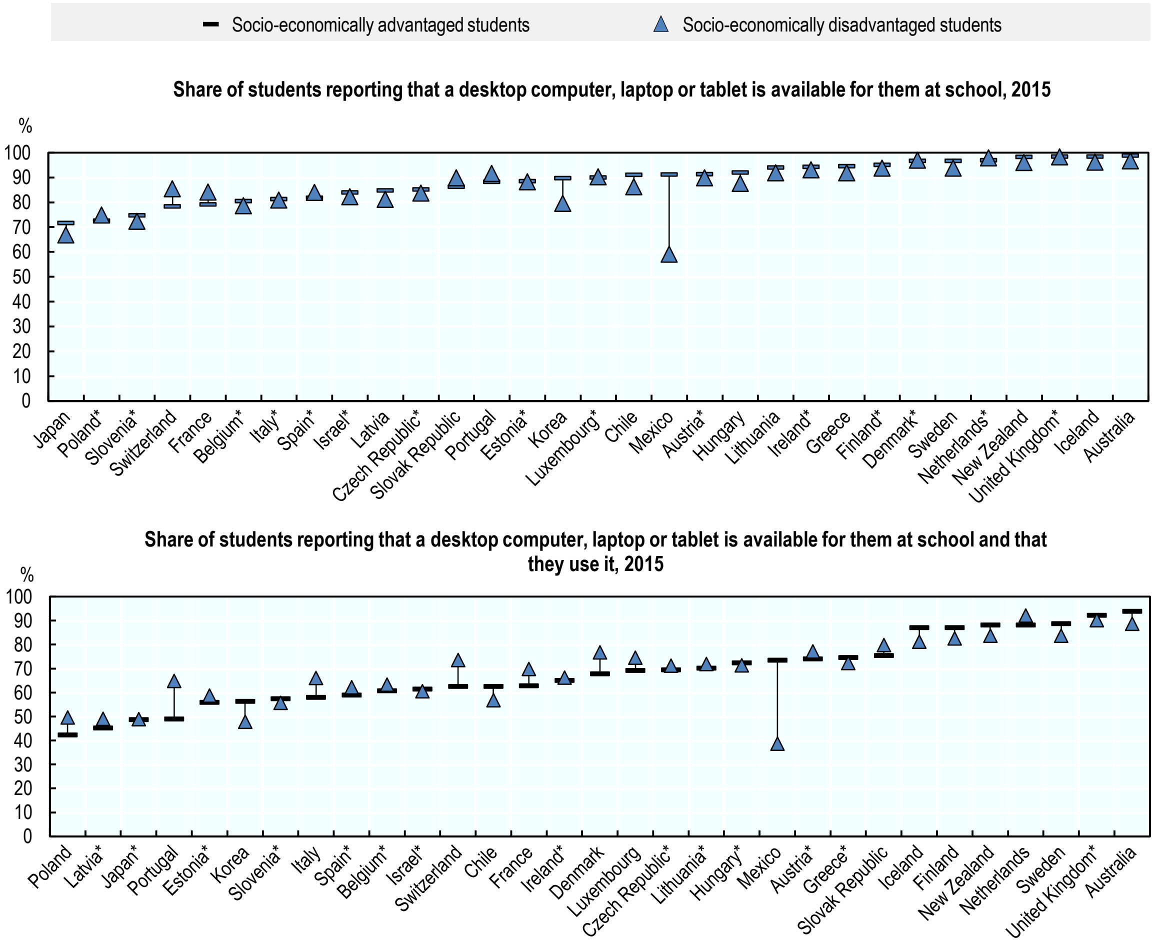
Across the OECD, socio-economically disadvantaged students have similar access to ICT devices in schools as advantaged ones and in a few countries, they tend to use these devices more (Figure 5.3). Providing access to the Internet and ICT infrastructure has been a goal of education policies in many OECD countries, to compensate for income inequalities and lower access to computers at home among socio-economically disadvantaged students (OECD, 2015[7]; Bulman and Fairlie, 2016[8]). The digital divide in terms of access to computers in schools appears therefore to have been largely bridged. A notable exception is Mexico, where significantly fewer disadvantaged students report having access to desktop computers, laptops or tablets at school. Moreover, fewer than 40% of socio-economically disadvantaged students in Mexico report using computers available in schools, in comparison to more than 70% of advantaged students. These data do not capture, though, potential differences in the quality of digital infrastructure available in schools for disadvantaged and advantaged students.

Figure 5.3. Computer access and use in schools, by students' socio-economic status



Share of students reporting that a desktop computer, laptop or tablet is available for them at school, 2015

Share of students reporting that a desktop computer, laptop or tablet is available for them at school and that they use it, 2015

Note: Students are considered to be socio-economically advantaged if they are among the 25% of students with the highest values on the PISA ESCS index in their country or economy. Students are considered to be socio-economically disadvantaged if their values on the PISA ESCS index are among the bottom 25% within their country or economy. The sign "*" indicates that the difference between socio-economically advantaged and socio-economically disadvantaged students is not statistically significant at the 5% level.

Source: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

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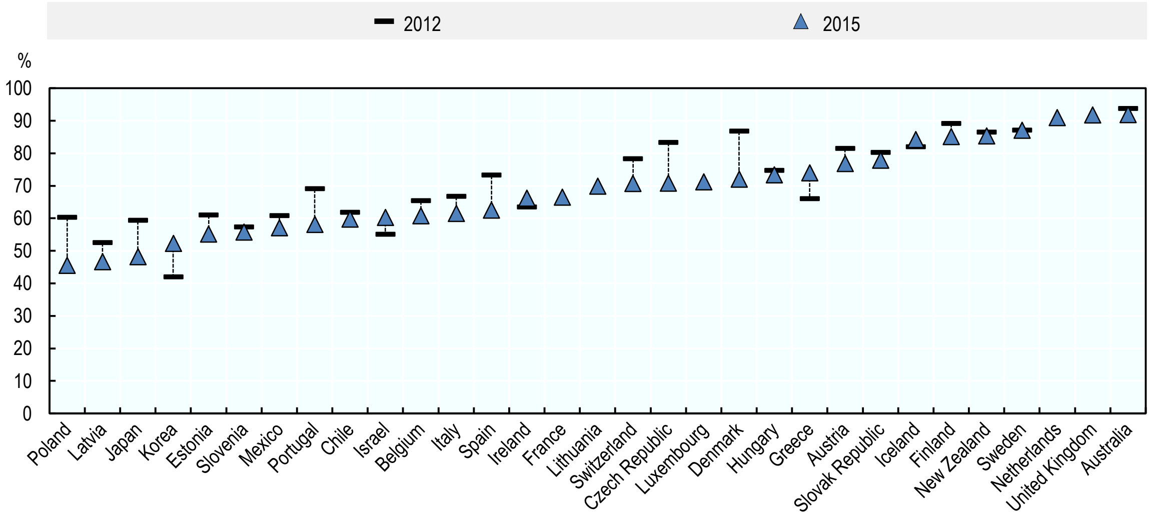
With few exceptions, the share of students relying on digital devices available at school has been stable or has even declined across OECD countries (Figure 5.4). The progressive introduction of more modern forms of ICT infrastructure, such as laptops and more recently tablets, has not been sufficient to compensate for the decline in the use of desktop computers (Figure 5.5). At the same time, these figures cannot capture whether students make use of their own mobile devices while in class or more generally at school.[1]

Figure 5.4. Computer use at school in 2015 and before

Share of students reporting that a desktop computer, laptop or tablet is available for them at school and that they use it



Sources: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/ and OECD (2012[9]), *PISA database 2012*, www.oecd.org/pisa/pisaproducts/pisa2012database-downloadabledata.htm.

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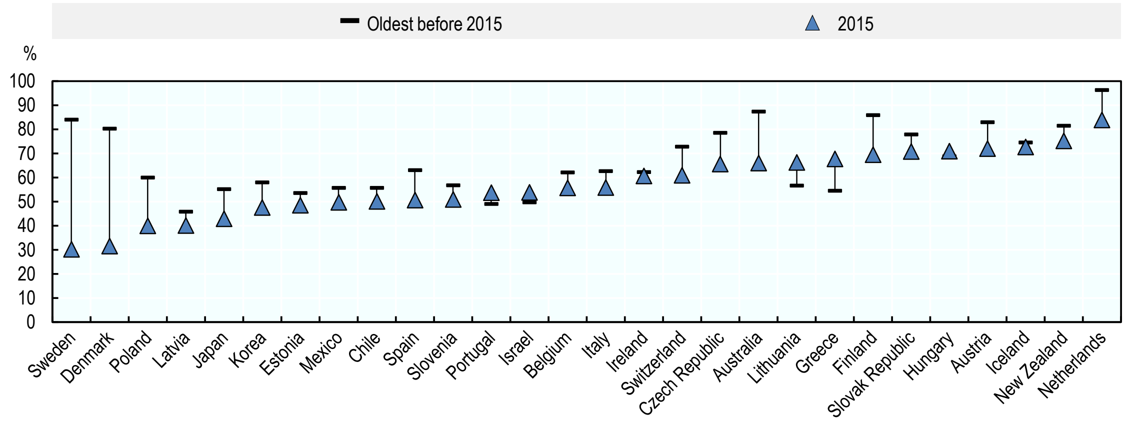
While fewer students report using the computers, tablets or laptops available in their school, the use of digital devices at school has risen. The index of ICT use summarises the frequency of digital device use for a variety of activities at school, from chatting or playing simulations to doing homework on school computers and practicing skills. Such digital devices may be part of the school infrastructure or may belong to students (e.g. smartphones). Across all OECD countries participating in the PISA ICT questionnaire, students use digital devices at school more often than before and the intensity of use appears to have accelerated in countries where students were already employing digital devices regularly (Figure 5.6). The frequency of digital device use at school is similar for socio-economically advantaged and disadvantaged students, except in Mexico and Australia.

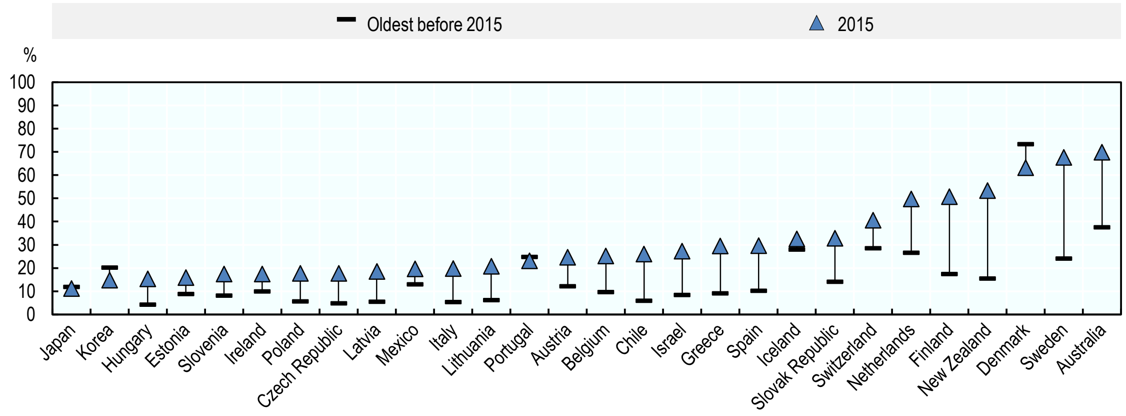
A surge in chatting online at school has triggered the overall rise in the frequency of digital device use at school (Figure 5.7): the share of students reporting that they chat at school at least once per week more than doubled between 2012 (18% of students) and 2015 (42% of students). Among digital activities taking place at school at least once per week, browsing the Internet for schoolwork is most recurrent among students in OECD countries (48% of students report browsing), followed by chatting (41%) and sending emails (28%).

Figure 5.5. Desktop computer, laptop and tablet use in schools in 2015 and before

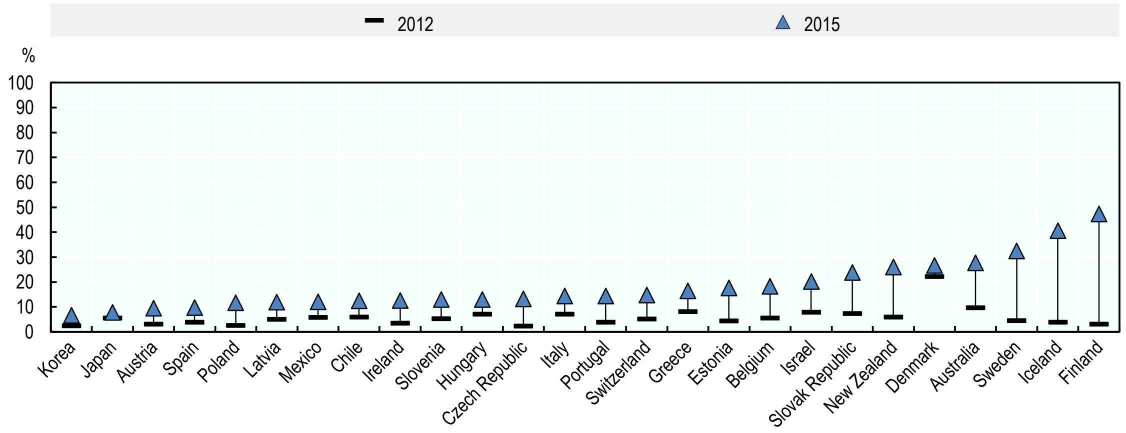
Share of students reporting that a desktop computer is available for them at school and that they use it



Share of students reporting that a laptop is available for them at school and that they use it



Share of students reporting that a tablet is available for them at school and that they use it



Note: Oldest before 2015 means: 2012 – for Mexico, 2009 – for all other countries. PISA (2009) did not include tablets in the list of available digital devices for students' use at school. Therefore, PISA (2015) data is contrasted with PISA (2012) data in the bottom panel of the figure.

Sources: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/, OECD (2012[9]), *PISA database 2012*, www.oecd.org/pisa/pisaproducts/pisa2012database-downloadabledata.htm and OECD (2009[10]), *PISA database 2009*, http://www.oecd.org/pisa/pisaproducts/.

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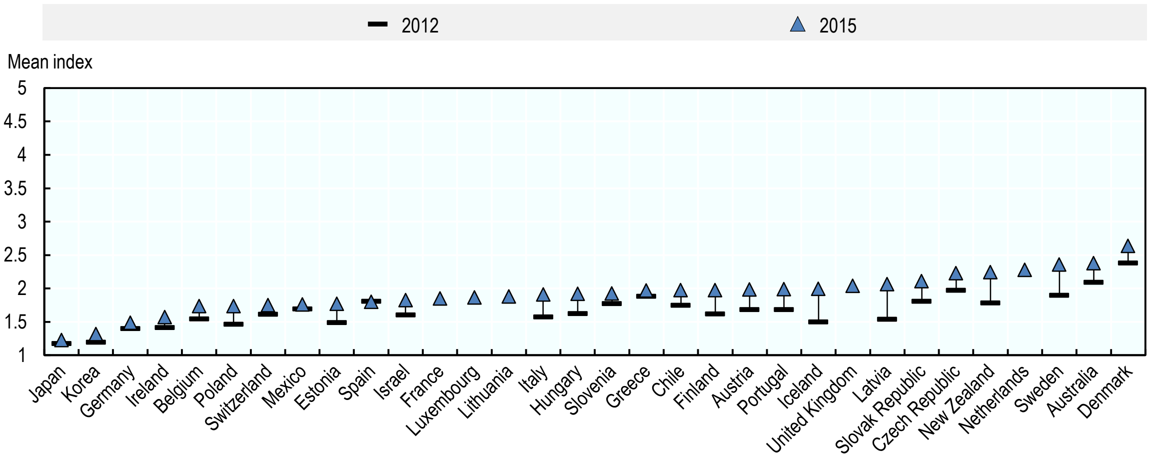
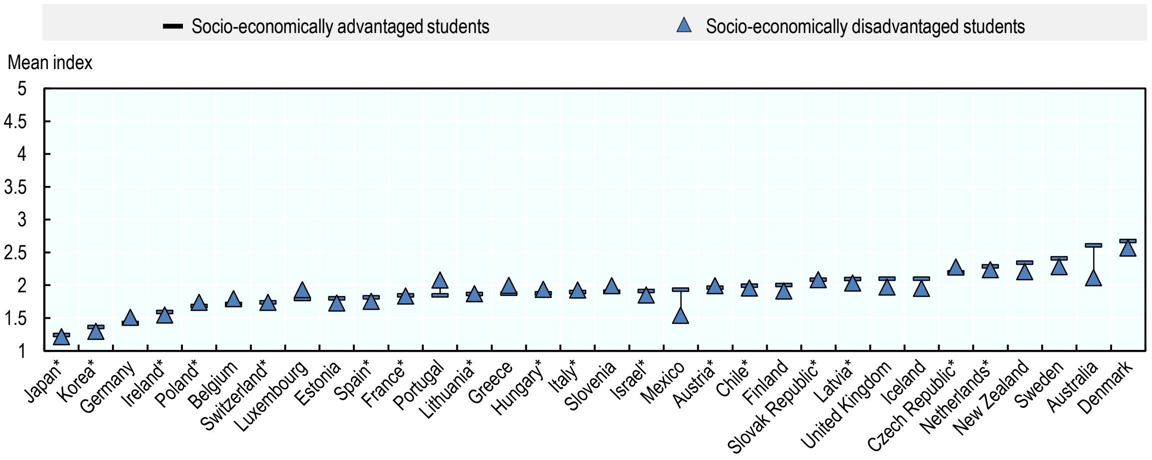
Figure 5.6. Index of ICT use at school

Mean index of ICT use at school, by year



Mean index of ICT use at school in 2015, by students' socio-economic status



Note: The figure displays the mean index of ICT use at school, by country and year (top panel) as well as by country and students' socio-economic status (bottom panel). The index of ICT use at school measures how frequently students make a variety of digital device uses at school: playing simulations; posting one's work on the school website; practicing and drilling (such as for foreign languages or mathematics); downloading, uploading or browsing material from the school's website or intranet; chatting online at school; using email at school; doing homework on a school computer; using school computers for group work and communication with other students; browsing the Internet for schoolwork. The frequency of uses goes from never or hardly ever (value of 1) to every day (value of 5). Socio-economically advantaged and disadvantaged students are defined in the note of Figure 5.3. The sign "*" indicates that the difference between socio-economically advantaged and socio-economically disadvantaged students is not statistically significant at the 5% level.

Sources: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/ and OECD (2012[9]), *PISA database 2012*, www.oecd.org/pisa/pisaproducts/pisa2012database-downloadabledata.htm.

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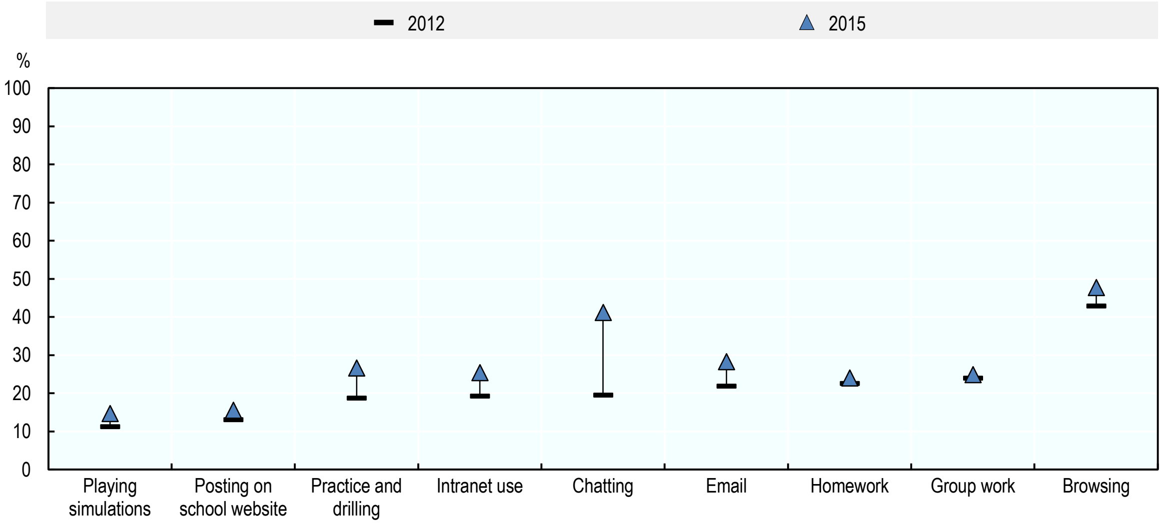
Figure 5.7. Uses of digital devices at school in 2012 and 2015

Share of students reporting to make a given use of digital devices at school at least once per week



Note: At least once per week means that students make given uses of digital devices once or twice a week, almost every day or every day. The sample includes all OECD countries participating in PISA (2012) and PISA (2015).
Sources: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/ and OECD (2012[9]), *PISA database 2012*, www.oecd.org/pisa/pisaproducts/pisa2012database-downloadabledata.htm.

StatLink https://doi.org/10.1787/888933974235

These first statistics suggest that technology may not be used to its full potential in schools. The fall in the use of ICT infrastructure available in schools coincides with the rise in the frequency of uses such as chatting, implying that students may simply be using their own mobile devices more for personal uses (e.g. instant messaging with friends) during school time. On the contrary, uses that would more naturally be associated with instruction activities (e.g. doing homework on a school computer or using computers for group work) have experienced only moderate increases.

The potential of new technologies for students' outcomes

New technologies hold promise for enhancing learning and developing skills that enable people to make the most of the digital society. Digital tools extend the learning universe outside the physical premises of the school. They allow personalised instruction that enables students to progress at their own pace and teachers to spend more time with learners who are lagging behind (Barrow, Markman and Rouse, 2009[11]). Technology is likely to change the content and sources of knowledge: traditional textbooks and curricula may be supplemented by educational software, online courses or digital textbooks. These expand the opportunities young learners have to find information and practice skills (OECD, 2016[12]), including the digital competencies required for sustainable use of new technologies (Box 5.1). At school and education system levels, new digital devices can be used for connected learning and exchange of teaching practices, to collect better student data for more rapid and better-targeted student feedback, and to bring instruction to isolated areas.

Digital competencies

Not all young learners are technological savvy (OECD, 2015[7]; Kennedy et al., 2010[13]) so the use of digital devices in schools can enhance students' digital skills. Student assessments rarely measure computer competencies, however, so there is little evidence on the impact of technology use in schools on students' digital skills, although a few studies find positive effects (Bulman and Fairlie, 2016[8]).

Box 5.1. Developing digital skills: Country examples

There is no widely agreed, comprehensive definition of digital skills, in part because technology is constantly advancing.

The Broadband Commission for Sustainable Development – a joint initiative of the International Communication Union and UNESCO – regards digital skills as a continuum from basic to advanced skills:

- Basic functional digital skills allow people to access and use digital technologies (e.g. understanding basic ICT concepts, being able to manage computer files, use keyboards or touch-screen devices).
- Generic/intermediate digital skills allow people to use technologies in meaningful and beneficial ways (e.g. using work-related software, creating online content, evaluating online risks).
- Advanced skills are those needed by ICT specialists (e.g. programming, app development) (Broadband Commission for Sustainable Development, 2017[14]).

Frameworks of digital competence

Generic/intermediate digital skills are often at the core of national digital strategies or policies that seek to develop the population's digital literacy or competence. Frameworks of digital competence can help assess not only the levels and types of skills, but also the attitudes and knowledge individuals have or should develop in the digital area (Broadband Commission for Sustainable Development, 2017[14]).

The European Commission has designed a digital competence framework that broadly defines digital competence as "the confident, critical and creative use of ICT to achieve goals related to work, employability, learning, leisure, inclusion and/or participation in society" (Ferrari, 2013[15]). Its typology identifies five areas of digital competence (each of which contain knowledge, skills and attitude dimensions): information and data literacy, communication and collaboration, digital content creation, safety and problem solving. Proficiency levels for these areas are assessed based on the complexity of tasks, the autonomy with which the individual can perform these tasks and the cognitive domain (remembering, understanding, applying, and creating).

At the school level, an example of a framework for digital competence is the one put forward by the Australian Curriculum, Assessment and Reporting Authority (ACARA). Students who develop an ICT capability are students who "learn to use ICT effectively and appropriately to access, create and communicate information and ideas, solve problems and work collaboratively in all learning areas at school and in their lives beyond school" (ACARA, n.d.[16]).

For ACARA, ICT capability development is organised around several dimensions: managing and operating ICT (e.g. managing data, selecting and using software), communicating with ICT, creating with ICT (e.g. using ICT to generate ideas or manage digital solutions for issues arising in learning activities), investigating with ICT (e.g. finding and analysing information, verifying sources and reliability of digital data), and applying social and ethical protocols and practices when using ICT (e.g. recognising intellectual property, applying personal security protocols).

Students' proficiency is assessed in all these dimensions and across all school years, since the development of ICT capability is considered as a learning continuum (ACARA, n.d.[17]). At the same time, ICT capability supports student learning in all subjects covered by the curriculum, for instance by using digital tools to create artworks, looking for and critically analysing online information about historical events, or investigating mathematical concepts using multimodal technologies. A Digital Technologies learning area is also part of the curriculum, focusing specifically on "understanding the characteristics of data, digital systems, audiences, procedures and computational thinking" (ACARA, n.d.[16]).

Developing digital skills and competence in schools

In many countries, the development of digital skills in schools has relied primarily on ICT or computational science classes. The framework developed by ACARA is an example of a progressive move from developing digital skills as part of stand-alone ICT classes, to a more comprehensive approach in which digital skills are also fostered in other learning areas. There is a risk, however, that developing digital skills by integrating technology across different subjects may result in uneven levels of technology use across classes or schools (Praxis, 2017[18]).

In France, a mandatory course on computational sciences and technology will be introduced in 2019, with the objective not only of teaching ICT as a science but also of discussing the role of digital technologies in society (Ministère de l'Éducation nationale et de la Jeunesse, 2018[19]). The government is also encouraging the creation of coding workshops outside classes and will progressively introduce a certification of digital skills for students in their last secondary school year.

In Canada, several provincial governments have adopted a comprehensive approach to digital competence (Hoechsmann and DeWaard, 2015[20]). For example, the government of Manitoba has put the focus on developing "literacy with ICT", which spans all curricular areas. In a similar vein to the ACARA framework, literacy with ICT requires "thinking critically and creatively, about information and about communication, as citizens of the global community, while using ICT safely, responsibly and ethically" (Manitoba Education and Training, n.d.[21]). Students are assessed based on a developmental learning continuum.

Between 2012 and 2016, Estonia implemented the ProgeTiger programme, aimed at preschool, primary and vocational education students (HITSA Information Technology Foundation in Education, n.d.[22]). The programme's aim was to enhance the digital competence of students by integrating technology education in the curriculum, by training teachers and by financing ICT infrastructure acquisition by schools (Conrads et al., 2017[23]). The programme required teachers to integrate technology in different subjects, allowing them to choose the type of technology they would use. Teachers had access to face-to-face and online training, and benefited from the support of local networks related to the programme.

Sources: Broadband Commission for Sustainable Development (2017[14]), *Working Group on Education: Digital Skills for Life and Work*, https://unesdoc.unesco.org/ark:/48223/pf0000259013 (accessed on 13 December 2018); Ferrari, A. (2013[15]), *DIGCOMP: A Framework for Developing and Understanding Digital Competence in Europe*, http://dx.doi.org/10.2788/52966; ACARA (n.d.[16]), *Information and Communication Technology (ICT) Capability*, https://www.australiancurriculum.edu.au/f-10-curriculum/general-capabilities/information-and-communication-technology-ict-capability/ (accessed on 17 May 2018); ACARA (n.d.[17]), *Information and Communication Technology Capability Learning Continuum*, https://www.australiancurriculum.edu.au/media/1074/general-capabilities-information-and-communication-ict-capability-learning-continuum.pdf (accessed on 14 December 2018); Praxis (2017[18]), *ICT Education in Estonian Schools and Kindergartens*, http://www.praxis.ee/en/works/ict-education-in-estonian-schools-and-kindergartens/ (accessed on 14 December 2018); Ministère de l'Éducation nationale et de la Jeunesse (2018[19]), *Le numérique au service de l'École de la confiance*, http://www.education.gouv.fr/cid133192/le-numerique-service-ecole-confiance.html (accessed on 14 December 2018); Hoechsmann, M. and H. DeWaard (2015[20]), *Mapping Digital Literacy Policy and Practice in the Canadian Education Landscape*, http://mediasmarts.ca/teacher-resources/digital-literacy-framework/mapping-digital-literacy-policy-practice-canadian-education-landscape (accessed on 14 December 2018); Manitoba Education and Training (n.d.[21]), *Literacy with ICT - What is LwICT?*, https://www.edu.gov.mb.ca/k12/tech/lict/what/index.html (accessed on 14 December 2018); HITSA Information Technology Foundation in Education (n.d.[22]), *ProgeTiger Programme*, https://www.hitsa.ee/it-education/educational-programmes/progetiger (accessed on 14 Decembe r 2018); Conrads, J. et al. (2017[23]), *Digital Education Policies in Europe and Beyond: Key Design Principles for More Effective Policies*, http://dx.doi.org/10.2760/462941.

As technologies evolve at an ever-faster pace, it is essential for people to acquire more general digital literacy skills rather than specialised ones that risk rapidly becoming obsolete. In an increasingly digitalised society, individuals should be able to interpret the information provided by digital tools in specific contexts, adapt to an expanding number and types of tools, protect their data and privacy, and develop their own digital content (Carretero, Vuorikari and Punie, 2017[24]). Schools can help develop such skills from an early age and empower students to become not only critical users of new technologies, who understand the inherent mechanisms and risks of technology, but also creators of digital material and maybe of tools that serve their purposes (Bell, 2016[25]).

This translates into a need to move beyond traditional ICT classes, which teach students how to use specific software, and into the domain of computational thinking (Box 5.2) (Bocconi et al., 2016[26]).

Box 5.2. Computational thinking, computer programming and coding

Computational thinking frames problems in ways that computers can help solve them (Wing, 2006[27]; CSTA/ISTE, 2011[28]; Paniagua and Istance, 2018[29]). It requires algorithmic thinking, problem decomposition, logical reasoning and abstraction (Voogt et al., 2015[30]; Bell, 2016[25]; Paniagua and Istance, 2018[29]). In this respect, it is closely related to mathematics and computer science reasoning. Early research on computational thinking presented it as a "universally applicable attitude and skill set everyone, not just computer scientists, would be eager to learn and use" (Wing, 2006[27]). The focus of computational thinking is thus not on technology use per se, but rather on understanding the underlying notions and mechanisms of digital technologies (Bocconi et al., 2016[26]).

Computational thinking can be taught through computer programming, the process of instructing a computer to carry out specific tasks (Balanskat and Engelhardt, 2015[31]). While programming, students are exposed to computational thinking and solve problems with the help of computers (Lye and Koh, 2014[32]). One of the first programming experiences in schools was that of Logo programming for teaching mathematics in the 1960s (Feurzeig, Papert and Lawler, 2010[33]) and many newer programming languages (e.g. Alice, Scratch) are based on Logo (Lye and Koh, 2014[32]).

Computer programming and coding are often used as similar notions. However, coding refers more precisely to the writing in a specific programming language of instructions the computer has to perform (Balanskat and Engelhardt, 2015[31]). Programming is therefore a wider concept than coding, since it involves the more general analysis, development and implementation of a solution to problems using a computer (Lye and Koh, 2014[32]; Bocconi et al., 2016[26]).

Sources: Wing, J. (2006[27]), *Computational Thinking*, https://www.cs.cmu.edu/~15110-s13/Wing06-ct.pdf (accessed on 09 April 2018); CSTA/ISTE (2011[28]), *Computational Thinking. Teacher Resources*, http://www.iste.org/docs/ct-documents/ct-teacher-resources_2ed-pdf.pdf?sfvrsn=2 (accessed on 27 March 2018); Paniagua, A. and D. Istance (2018[29]), "Teachers as Designers of Learning Environments: The Importance of Innovative Pedagogies", https://www.oecd-ilibrary.org/education/teachers-as-designers-of-learning-environments_9789264085374-en; Voogt, J. et al. (2015[30]), "Computational thinking in compulsory education: Towards an agenda for research and practice", http://dx.doi.org/10.1007/s10639-015-9412-6; Bell, T. (2016[25]), *What's All the Fuss About Coding?*, https://research.acer.edu.au/cgi/viewcontent.cgi?article=1288&context=research_conference (accessed on 27 March 2018); Bocconi, S. et al. (2016[26]), *Developing Computational Thinking in Compulsory Education – Implications for Policy and Practice*, http://dx.doi.org/10.2791/792158; Balanskat, A. and K. Engelhardt (2015[31]), *Computing Our Future. Computer Programming and Coding. Priorities, School Curricula and Initiatives across Europe*, http://fcl.eun.org/documents/10180/14689/Computing+our+future_final.pdf/746e36b1-e1a6-4bf1-8105-ea27c0d2bbe0 (accessed on 29 March 2018); Lye, S. and J. Koh (2014[32]), "Review on teaching and learning of computational thinking through programming: What is next for K-12?", http://dx.doi.org/10.1016/J.CHB.2014.09.012; Feurzeig, W., S. Papert and B. Lawler (2010[33]), "Programming-languages as a conceptual framework for teaching mathematics http://dx.doi.org/10.1080/10494820903520040.

Computational thinking does not necessarily imply the use of computers, but it can occur in the context of programming. In a similar vein, computational thinking may be taught as a subject in itself or it may be incorporated as a tool for the study of other subjects.

When students are exposed to computational thinking through programming, they can increase both their problem-solving and digital competencies, as well as acquire a deeper understanding of the underlying mechanisms and concepts of new technologies. Promising research shows that computational thinking activities have the potential to develop both specific academic skills (e.g. in mathematics) as well wider 21st century skills, including creativity, digital literacy or critical thinking (Lye and Koh, 2014[32]; Paniagua and Istance, 2018[29]).

Academic performance

Simply providing access to digital tools or using them in the classroom does not automatically lead to better academic results, even if investment in ICT does not crowd out resources allocated to other inputs (Bulman and Fairlie, 2016[8]; Escueta et al., 2017[34]). This suggests that programmes aiming at merely increasing availability of digital devices for students do not increase instruction time, but rather substitute more efficient traditional instruction with time devoted to computer use (Angrist and Lavy, 2002[35]; Leuven et al., 2007[36]; Cristia et al., 2017[37]). When academic performance did improve, this was mostly at to schools that had benefitted from the largest increases in ICT investment and were also already able to use ICT infrastructure more efficiently (Machin, Mcnally and Silva, 2007[38]). Such schools already had Internet access and hence may have concentrated the additional investment on teacher training and support.

In a similar vein, the impact of computer-assisted instruction (or educational software) on academic performance depends on whether such technology is used as a substitute or a complement to traditional instruction, and if it is used as a substitute, of the quality of the traditional method it substitutes. The use of such technology in schools may improve students' performance more in developing countries than in developed ones if it replaces traditional instruction of lower quality or compensates for a lack of teachers (Banerjee et al., 2007[39]; The Economist, 2018[40]).

Focusing on specific school subjects, computer-assisted instruction technologies that help engage students in practicing their mathematics skills have shown more promising results (Barrow, Markman and Rouse, 2009[11]; Roschelle et al., 2010[41]; Roschelle et al., 2016[42]). For reading, traditional computer-assisted programmes have only a moderate impact but programmes that combine computer and non-computer instruction with teacher professional development appear to be more effective (Cheung and Slavin, 2012[43]).

The role of pedagogies

Irrespective of the subject in which it is used, technology has the most positive effects when used as an amplifier for teaching, enabling teachers and students to relate the knowledge and skills developed in traditional and non-traditional instruction (OECD, 2015[7]; Paniagua and Istance, 2018[29]; Peterson et al., 2018[44]). When technology is blended in innovative teaching and learning methods, it can boost student performance and enhance student motivation (Fleischer, 2012[45]; Paniagua and Istance, 2018[29]; Peterson et al., 2018[44]).

Technology cannot achieve its full potential in classrooms if it is used merely to reproduce traditional practices and pedagogies. If such practices are already insufficient to raise student outcomes, then relying on technology only replicates the same results. Technology can even have detrimental effects if it results in distraction or cognitive overload or otherwise frustrates students' learning needs (Paniagua and Istance, 2018[29]; Peterson et al., 2018[44]) .

Innovative uses of digital tools and devices show great promise for teaching and re-engaging those who face difficulties at school. There are many examples of such pedagogical methods, including gamification, which integrates the pedagogical principles of play and games (including video games) in formal learning, or flipped classes, in which students are required to attain content, usually provided by ICT material, before the class.

Pedagogies are therefore of crucial importance for making the most of new technologies in schools (Table 5.1). They should rely on technology as a tool for enhancing student motivation and learning, rather than treat technology use as an objective per se. Pedagogies ensure that digital uses correspond to learners' needs, prior competencies and digital literacy, following clear instructional designs. They encourage active learning, with teachers acting as mentors who guide students and help them remain focused on the learning elements of tasks. Finally, innovative pedagogies related to technology use put forward new ways of collaboration and learning (e.g. through the use of social networks), extending the learning process outside the school environment (Paniagua and Istance, 2018[29]; Peterson et al., 2018[44]).

Table 5.1. The role of pedagogies in shaping the use of new technologies in the classroom

Technology type	What pedagogies can do			
General ICT	Use ICT as a complement to teaching practices	Enhance motivation "through" and not "to" technology	Promote digital literacy and ensure students have prior competences to use digital tools	Encourage active learning and collaboration
Multimedia materials	Use sound instructional designs	Encourage multimedia authoring as a tool for thinking skills, communication and self-expression development	Accompany students, scaffolding the use of materials	Ensure contents can be understood and learners can stay focused
Multi-tasking and interactive environments	Enhance awareness of multi-tasking and of its consequences	Design and implement environments based on sound pedagogical approaches	Address harmful multi-tasking	Promote the use of knowledge frameworks to help students connect new information with prior knowledge
Gaming	Ensure the integration of video games into the instructional context	Ensure exploration and manipulation of realistic scenarios	Ensure students focus on the learning elements of games	Provide feedback to students and align games to their learning capacity
Collaborative and Web 2.0 environments	Ensure Web 2.0 principles are followed (e.g. student-generated content, interaction and collaboration)	Avoid transmission of content by the teacher/ relegation of students to passive roles	Enhance students' capacities to self-regulate and remain focused	Put forward new ways of collaboration and learning based on Web 2.0 tools, extending learning outside the classroom

Note: General ICT refers to digital technology (e.g. computers, smartphones, and software). Multimedia materials refer to combinations of verbal and non-verbal technology-based content (e.g. video clips, e-books, and PowerPoint slides). Multi-tasking and interactive environments refer to the performance of different tasks at the same time (e.g. watching videos, reading online, and sending messages) in environments that are responsive to users' actions. Gaming environments refer to the use of video games in school settings. Collaborative and Web 2.0 environments refer to the use of digital tools for collaborative and social activities (e.g. blogs, social networking sites, and wikis).

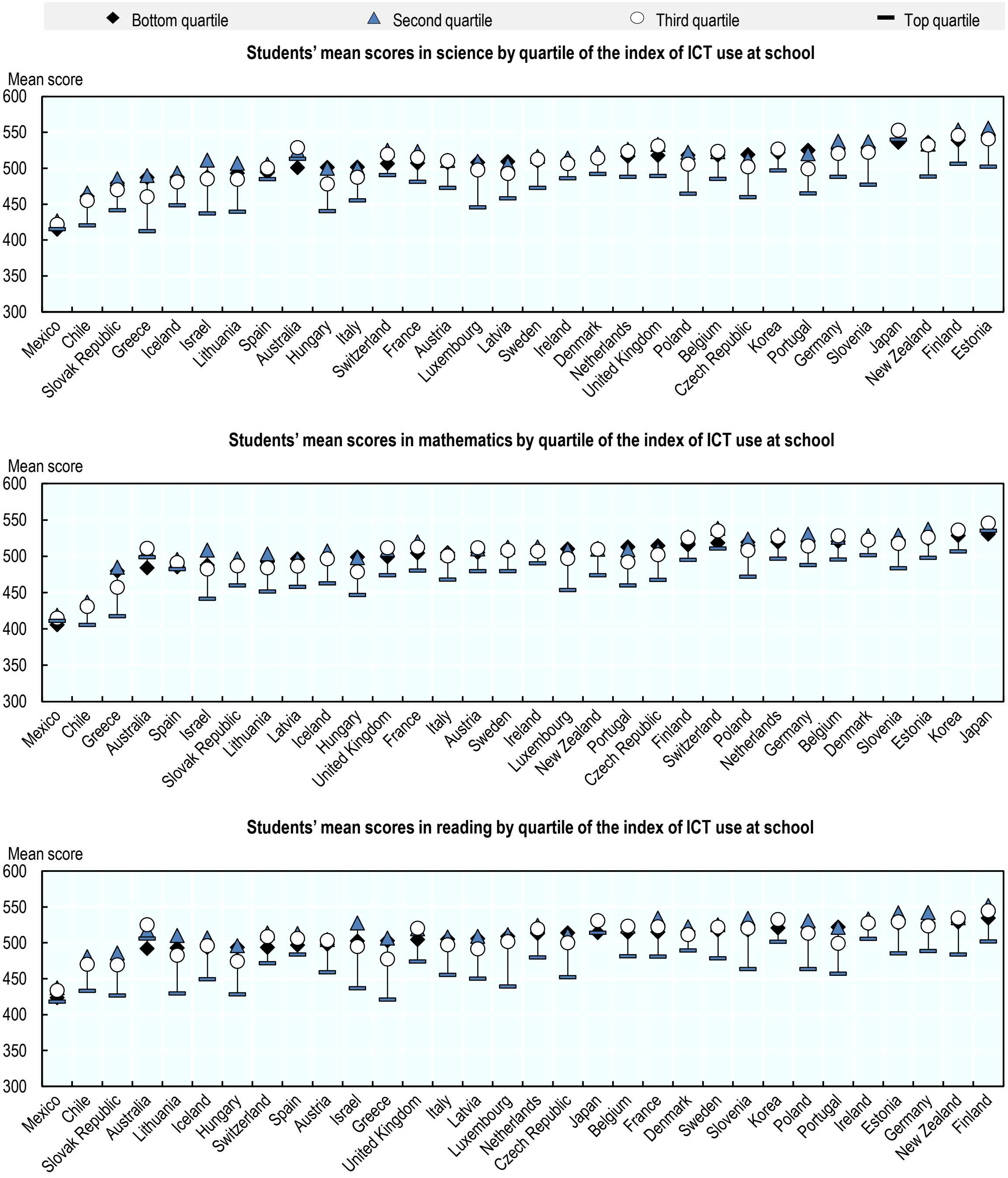
Source: Peterson et al. (2018[44]), "Understanding innovative pedagogies: Key themes to analyse new approaches to teaching and learning", https://www.oecd-ilibrary.org/education/understanding-innovative-pedagogies_9f843a6e-en.

In practice: The impact of technology use in schools

Data from PISA 2015 show that when levels of ICT use at school are very high, student performance tends to be lower, whether in science, mathematics or reading (Figure 5.8). The exception to this pattern is Australia, where students in the top quarter score perform better than those at the lower end of the distribution of ICT use. In the Australian curriculum, ICT use and the development of ICT capabilities are embedded at all learning levels and in all curriculum areas, not only in the technology-specific ones (Box 5.1). The objective is that students apply ICT knowledge and skills to meet learning requirements across a large range of subjects, from mathematics, to humanities, health and physical education (ACARA, n.d.[16]).

Results in collaborative problem-solving student assessments match these findings (OECD, 2017[46]), suggesting that extensive use of technologies at school may replace other, more efficient educational practices or may simply distract students. In many countries, disadvantaged schools have benefitted from substantial investments in ICT, but overall, this effect does not seem to explain the negative relationship between highly frequent ICT use and students' performance (Figure 5.9).

Figure 5.8. Index of ICT use at school and student performance in school subjects



Students' mean scores in science by quartile of the index of ICT use at school

Students' mean scores in mathematics by quartile of the index of ICT use at school

Students' mean scores in reading by quartile of the index of ICT use at school

Note: The figure displays students' mean scores in science (top panel), mathematics (middle panel) and reading (bottom panel), by quartile of the index of ICT use at school. The index of ICT use at school is defined in the note of Figure 5.6. Countries are ranked by the mean score of students in the bottom quartile of the index of ICT use at school.

Source: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

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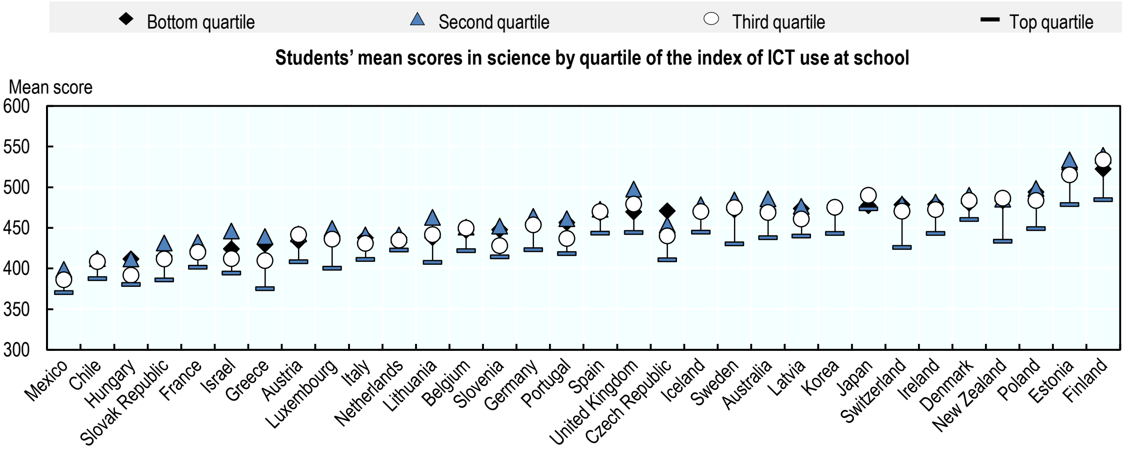
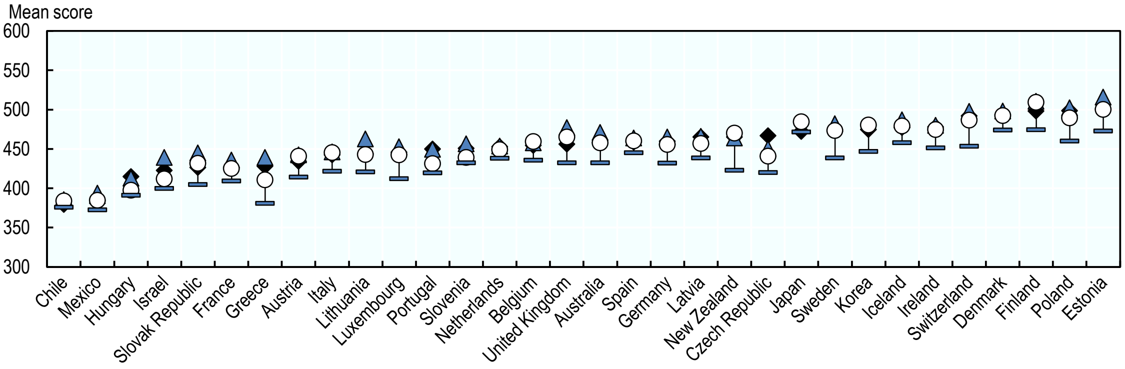
Figure 5.9. Index of ICT use at school and student performance in school subjects in socio-economically disadvantaged schools

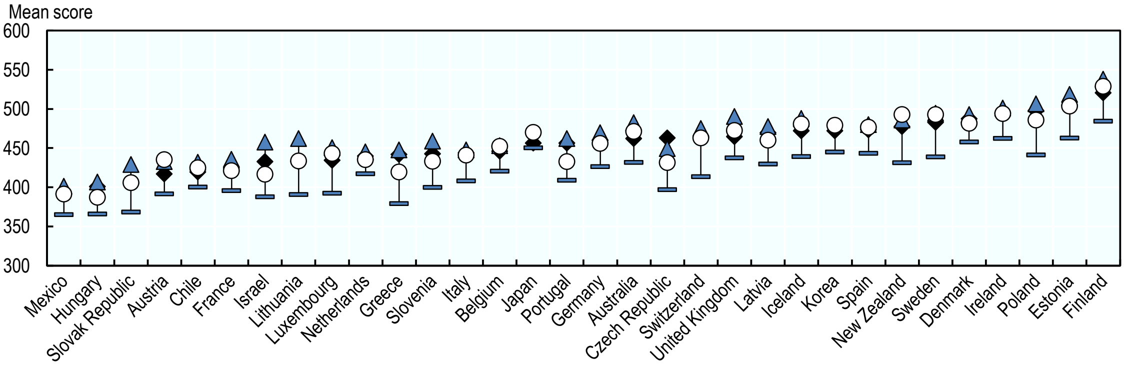


Students' mean scores in science by quartile of the index of ICT use at school

Students' mean scores in mathematics by quartile of the index of ICT use at school



Students' mean scores in reading by quartile of the index of ICT use at school



Note: The figure displays students' mean scores in science (top panel), mathematics (middle panel) and reading (bottom panel), by quartile of the index of ICT use at school in socio-economically disadvantaged schools. In each PISA-participating education system, schools are divided into four groups with approximately an equal number of students (quarters), based on the average PISA index of economic, social and cultural status (ESCS) of their 15-year-old students. The index of ICT use at school is defined in the note of Figure 5.6. Countries are ranked by the mean score of students in the bottom quartile of the index of ICT use at school.
Source: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

StatLink https://doi.org/10.1787/888933974273

The effect of technology on student performance depends on how devices are used in the classroom. Some activities may be more effective in class when computers are used instead of traditional instruction techniques. The lack of any visible correlation between computer use and overall student performance would thus simply be the result of positive effects of computer use in some activities being offset by negative effects in others (Falck, Mang and Woessmann, 2015[47]; Comi et al., 2017[48]).

Analyses based on PISA data show that many types of frequent digital device use at school tend to accompany lower students' performance, whether in science, mathematics or reading (Figure 5.10). Playing simulations, posting work on the school website, using school computers for homework or group work at least once per week are all associated with lower test scores, even when socio-economic status and several other individual and school characteristics are accounted for. Test scores appear to be higher only for students who browse the Internet regularly for school work. Looking up for information may indeed be more efficiently done using a computer, while other activities – such as the practice of skills or even group work – can be performed equally well without the help of technology (Falck, Mang and Woessmann, 2015[47]).

Many digital device uses are likely to displace more efficient instructional activities when done with high frequency. Spending several hours per week posting work on the school website or working in groups on a computer is more likely to replace other more productive tasks than devoting ten minutes to browsing the Internet for school work. Moreover, effects are also likely to vary depending on whether specific uses are made within the class or not. Chatting appears to be less negatively related to school performance than playing simulations, but chatting may also be done during break time and hence not interfere with actual instruction. Additional information on teaching practices would help further refining these findings, as well as more data on the amount of time students devote to digital device uses at school, and more specifically within the classroom.

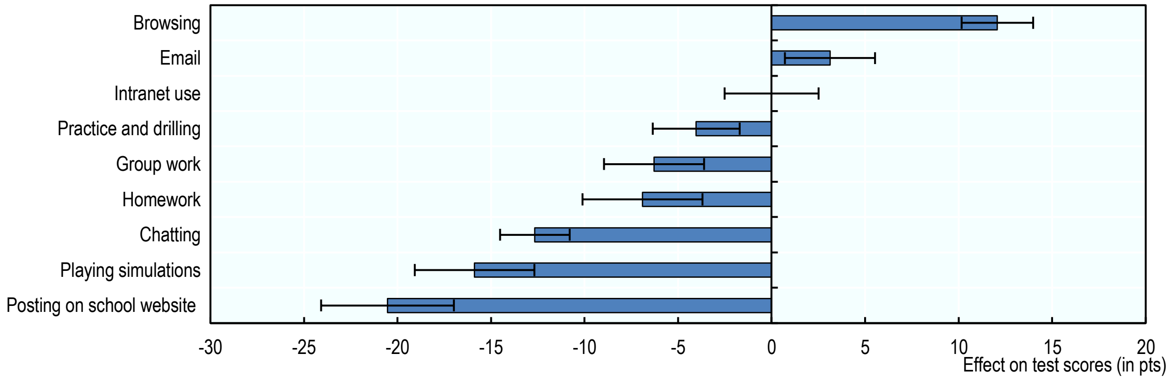
In addition, reliance on ICTs appears to be most recurrent in subjects that are already traditionally associated with the use of technology (Figure 5.11). In countries participating in TALIS, more than half of teachers in technology and almost half of those who teach practical and vocational skills classes rely on ICTs frequently for students' class work or projects. On the contrary, foreign languages and even science or mathematics teachers are less likely to do so, whether at the lower-secondary or upper-secondary levels. Digital tools are used mainly in subjects where they would be expected to be present, suggesting that innovative methods based on ICTs are still not common in schools. Many teachers still report using technologies primarily for administrative tasks and the preparation of lessons rather than as an integral part of their in-class teaching (European Commission, 2013[49]).

In this respect, technology use should be seen as an integrated tool in wider teaching and learning activities rather than an objective in itself or a direct route to academic improvement. ICT investments dedicated to teachers tend to accompany higher student performance than increases in the number of available computers for students (Denoël et al., 2017[50]).

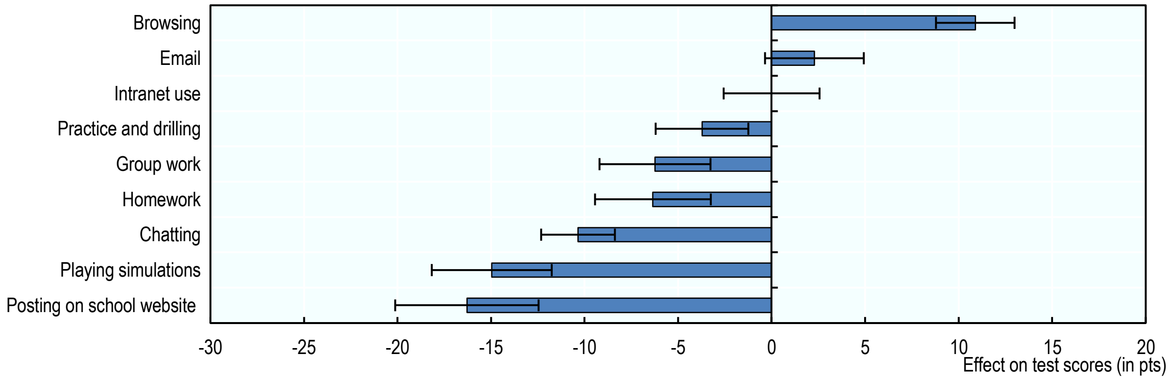
For technology to improve students' academic performance, both its quality and its co-ordination with other teaching practices and the curriculum are essential. Access to digital devices in schools is widespread in OECD countries, but the tools may not be adequate, sufficiently up-to-date or optimally used (Chatterji, 2017[51]).

Figure 5.10. Uses of digital devices at school and performance in school subjects, accounting for students' socio-economic status

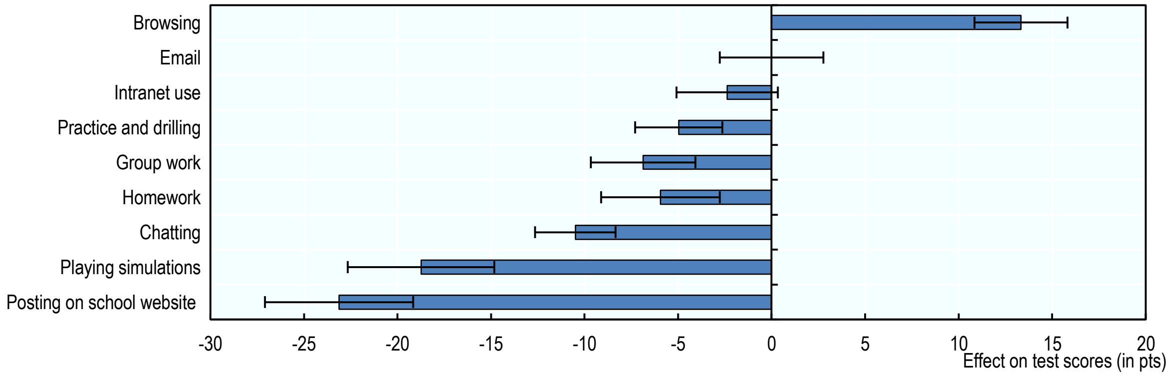
Effect of at least weekly ICT use at school on students' scores in science relative to less than weekly



Effect of at least weekly ICT use at school on students' scores in mathematics relative to less than weekly



Effect of at least weekly ICT use at school on students' scores in reading relative to less than weekly



Note: The figure displays estimated effects of at least weekly ICT use at school, by type of use, on student performance in: science (top panel), mathematics (middle panel) and reading (bottom panel). Bars display coefficients from a regression estimating the effect of various uses of digital devices at least once a week at school on students' performance. The different uses are binary variables equal to 1 if the student performs a given use at least once or twice per week at school and 0 otherwise. Regression controls include: the PISA index of student's socio-economic status, a dummy variable for disadvantaged schools, age, gender, immigration status, a dummy variable for attending a private school as well as a variable for living in a rural area. Country fixed effects are included in the regression. The error bars correspond to 1.96 standard errors and as such represent the 95% confidence interval. The sample includes all OECD countries participating in PISA (2015).

Source: OECD calculations based on OECD (2015[6]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

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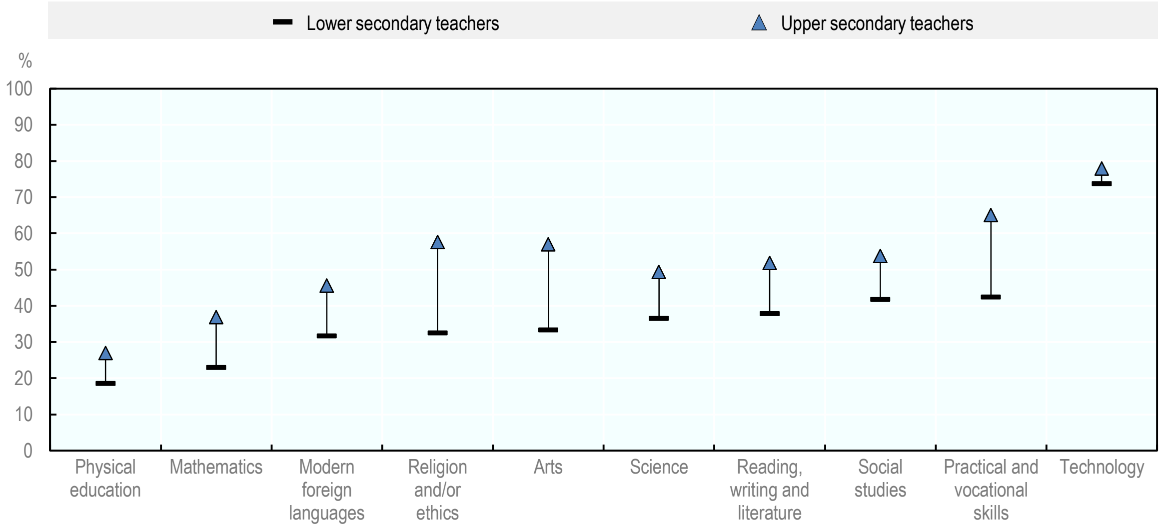
The results in this section emphasise the need to fundamentally rethink the use of new technologies for young learners in schools. Teachers are the people who are most aware of their students' needs. When decisions are made to adopt given technologies in schools, teachers could be consulted or allowed to choose between various types of technologies or digital tools. Professional development programmes in ICT use for teaching could be combined with higher availability of ICT support in schools. Assessing the efficiency of software or tools before adopting them at a large scale also need to be considered. More generally, governments should shift their focus from simply investing in resources to ensuring a tailored approach to technology use, in which teachers have the necessary ICT support and training to rely on digital tools.

Figure 5.11. Teachers with high ICT frequency use for students' projects or class work, by subject

Share of teachers with high ICT frequency for students' projects or class work, 2013



Note: High ICT frequency use occurs when ICTs are used frequently or nearly in all lessons for students' class work or projects. The sample for lower secondary teachers includes teachers from: Abu Dhabi (United Arab Emirates), Alberta (Canada), Australia, Brazil, Bulgaria, Chile, Croatia, Czech Republic, Denmark, England (United Kingdom), Estonia, Finland, Flanders (Belgium), France, Georgia, Israel, Italy, Japan, Korea, Latvia, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russian Federation, Serbia, Shanghai (China), Singapore, Slovak Republic, Spain, Sweden and United States. The sample for upper secondary teachers includes teachers from: Abu Dhabi (United Arab Emirates), Australia, Denmark, Finland, Italy, Mexico, Norway, Poland and Singapore. Weights have been rescaled so that each country contributes equally to the statistics.
Source: OECD calculations based on OECD (2013[52]), *TALIS database 2013*, http://www.oecd.org/education/school/talis-2013-results.htm.

StatLink https://doi.org/10.1787/888933974311

Teachers' use of new technologies

To ensure that students develop the skills they need for the future, it is vital that teachers are able to use appropriate and innovative pedagogical tools. Many of these tools and methods in turn rely on technology, making it crucial that teachers themselves are equipped with the skills required to use new technologies effectively (Paniagua and Istance, 2018[29]; Peterson et al., 2018[44]).

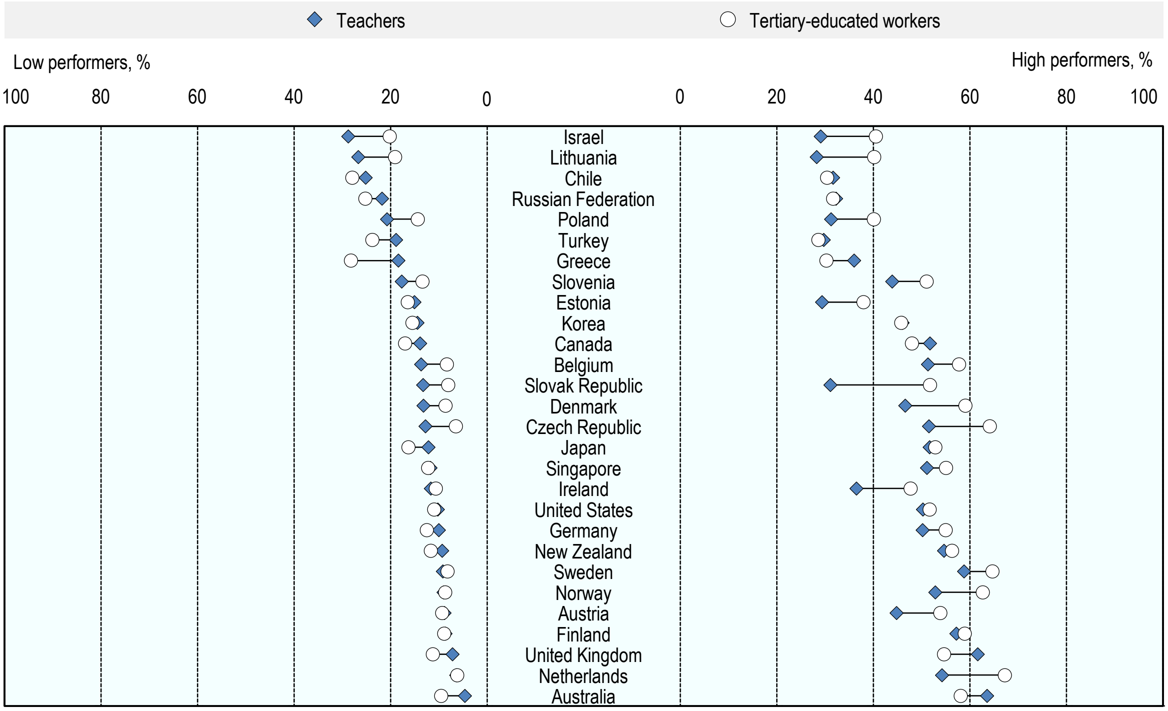
Teachers also have a role to play in raising students' awareness of the risks associated with new technologies and how to avoid them. As in other professions, teachers are also expected to have the necessary skills to make use of digital devices as part of their regular work, even outside the classroom.

Teachers' skills, motivations and attitudes are instrumental for the way ICTs are implemented in the classroom (Voogt et al., 2013[53]; European Commission, 2013[49]) and hence, for their own students' ability to make the most out of new technologies. To properly integrate ICTs in the classroom, teachers need not only basic digital skills that allow them to use a computer but also more complex digital skills that enable them to tailor the use of technology to their own teaching.

The Survey of Adult Skills (PIAAC) measures how adults, including teachers, can "use ICT tools and applications to assess, process, evaluate and analyse information in a goal-oriented way" (OECD, 2016[54]). The share of teachers with low problem-solving skills in technology-rich environments varies from less than 5% in Australia to around 20% or more in Chile and Turkey (Figure 5.12). Teachers appear to be as likely as other workers with a tertiary degree to have low skills in this area but less likely to have high skills. Australia displays the highest share of top performing teachers in problem solving in technology-rich environment (63.5%). It is also in Australia that high levels of ICT use in schools tend to be accompanied by high student performance (Figure 5.8).

Figure 5.12. Teachers' problem solving in technology-rich environment proficiency

Share of poor and top performing teachers and tertiary-educated workers in problem solving in technology-rich environments, by country (%)



Note: Teachers and tertiary-educated workers are defined based on the population of adults aged 25-65. Teachers are adults self-reporting working in the following two-digit occupations as classified by the International Standard Classification of Occupations (ISCO-08): Teaching Professionals (ISCO 23). Tertiary-educated workers are all adults in employment with a tertiary education as defined by 1997 International Standard Classification of Education (ISCED): Tertiary (ISCED 5B, 5A, 5A/6). Poor performers are defined as scoring at most *Below Level 1* (inclusive) in problem solving (including failing ICT core and having no computer experience), while top performers score at least *Level 2* (inclusive). Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933974330

Box 5.3. Teachers' problem-solving skills in technology-rich environments and students' digital performance: methodology

The analysis here is based on the methodology of (Hanushek, Piopiunik and Wiederhold, 2014[57]) who examined whether differences in teachers' cognitive skills (literacy and numeracy) among developed countries correspond with differences in student performance (in reading and mathematics). This section investigates the relationship between teachers' problem-solving skills in technology-rich environments (as measured in PIAAC 2012 and 2015) and students' digital performance (as measured by test scores in PISA 2012). It assumes that students assessed in PISA (2012) are likely to have been taught by teachers assessed in PIAAC (2012, 2015).

Students' and teachers' skills

Teachers in this analysis are adults who report that they are primary school teachers, secondary school teachers or other teaching professionals (e.g. special needs teachers, other music teachers). In a similar vein to (Hanushek, Piopiunik and Wiederhold, 2014[57]), the analysis excludes vocational education teachers and university professors since 15-year-olds assessed in PISA are unlikely to have been taught by these teachers.

Students' digital performance is measured through two assessments in PISA 2012: computer problem solving and computer mathematics. In PISA 2012, the assessment of computer problem solving focused on the fundamental cognitive processes that are essential for successful problem solving; only foundational ICT skills are required to take the test (OECD, 2013[58]). On the contrary, the computer-based assessment of mathematics included a variety of computer-based mathematics tools (e.g. statistical software, geometric construction and visualisation utilities, and virtual measuring instruments) among the assessment items (OECD, 2013[58]).

Empirical analysis

The analysis examines the extent to which differences in students′ test scores in computer problem solving and computer mathematics can be explained by cross-country differences in teachers′ problem-solving skills in technology-rich environments, when individual and school characteristics are accounted for. Teacher skills are the median of teachers' scores in problem solving in technology-rich environments at the country level. Both teachers' and students' scores are standardised across countries.

An ordinary least squares regression is estimated. One standard deviation increase in teachers' problem-solving skills in technology-rich environments is associated with higher student performance by 0.166 standard deviation in computer problem solving and by 0.175 in computer mathematics. Coefficients are statistically significant at the 1% level. Countries are given equal weights and robust standard errors are clustered at the country level. The estimation accounts for student, parent and school characteristics. Student characteristics include age, gender, migrant status, language spoken at home, number of books at home and an index of ICT availability at home. Parent characteristics include parents' labour market status, education levels and the ISCO-08 occupation code of the father. School characteristics include a dummy for whether the school is private or public, a dummy for whether the school is in a rural or in an urban area, the ratio of students and computers in school, the number of students in the school, an index for the degree of school autonomy and an index for teacher participation in school decisions. The index for the degree of school autonomy and the index for teacher participation in school decisions are defined in (OECD, 2014[59]).

Sources: Hanushek, E., M. Piopiunik and S. Wiederhold (2014[57]), "The value of smarter teachers: International evidence on teacher cognitive skills and student", http://www.nber.org/papers/w20727 (accessed on 13 April 2018); OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis; OECD (2013[58]), *PISA 2012 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*, http://dx.doi.org/10.1787/9789264190511-en; OECD (2014[59]), *PISA 2012 Technical Report*, https://www.oecd.org/pisa/pisaproducts/PISA-2012-technical-report-final.pdf (accessed on 09 April 2018).

Student achievement is closely tied with the quality of teachers (Barber and Mourshed, 2007[60]; Chetty, Friedman and Rockoff, 2014[61]; Hanushek, Piopiunik and Wiederhold, 2014[57]). Students' scores in computer problem solving and computer mathematics are related to teachers' problem-solving skills in technology-rich environments (Box 5.3). Many OECD countries would experience large increases in their students' digital performance were their teachers' problem-solving skills in technology-rich environments raised to the level of Australian teachers, the highest-performing ones in the sample (Figure 5.13). The magnitude of the relationship between teachers' and students' digital performance is similar to that between teachers' cognitive skills and students' scores in mathematics (Hanushek, Piopiunik and Wiederhold, 2014[57]).

The link between teachers' problem-solving skills and students' computer problem solving is likely to capture students' general capacity to solve problems rather than the ICT skills required for such tasks, since in PISA 2012 only basic ICT skills are required for this assessment. However, in the computer-based mathematics assessment, students are required to make use of a variety of digital equipment and software for mathematics. Hence, the relationship between students' scores in computer-based mathematics and teachers' problem-solving skills in technology-rich environments does capture the capacity to solve problems in a digital environment.

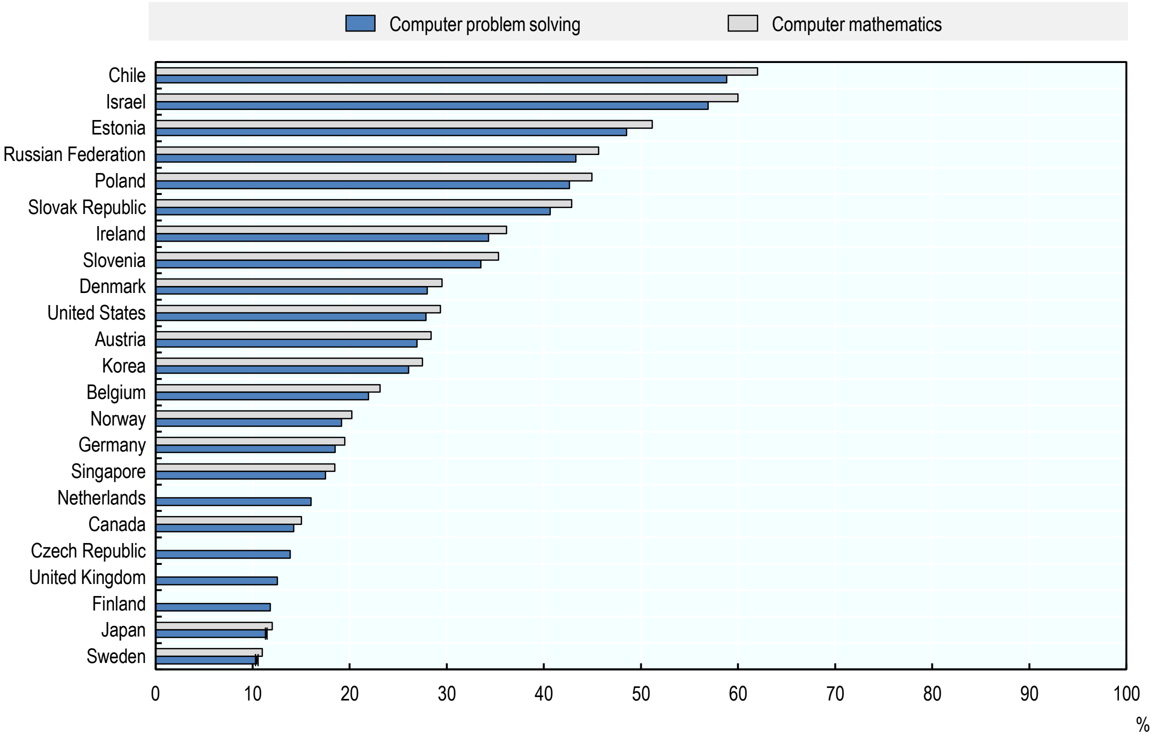
At work, teachers use ICTs with the same intensity as other high-skilled workers in many OECD countries. In countries where teachers' use of ICTs is low, it is below the use of ICTs by non-teacher workers with a similar level of education (Figure 5.14). Overall, teachers are required to make a sustained use of digital devices as part of their work. However, in 2013, only one third of teachers across countries included in the TALIS database used ICTs frequently as part of their regular teaching activities (Figure 5.15).

On average, teachers do not make a lot of use of technology for teaching activities but data from PIAAC show that this is not because their use of ICT decreases with age (Figure 5.16). However, these data do not distinguish between uses of digital devices inside the classroom and elsewhere at school (e.g. for administrative work). Data from TALIS focusing on the use of ICTs for students' projects or class work give a similar picture: the share of teachers using ICTs with high frequency in the classroom is almost constant across ages and experience levels. Upper secondary-level teachers make the biggest use of ICTs, as expected, reflecting either the capacity of students at these ages to make more mature uses of digital devices or the higher frequency of school subjects related to practical skills acquisition, which may rely more heavily on the use of technologies (Figure 5.11).

In most countries, more than 30% of teachers said they needed further training to perform their duties. In countries where the need for training among high-skilled workers is the largest (Austria, Chile, Germany, Lithuania, Slovenia), teachers are more likely than non-teachers to be in need of training (Figure 5.17).

Figure 5.13. Potential increase in computer problem solving and mathematics student scores linked to an increase in teachers' skills to the level of top performers

Increase in students' test scores (in % of international standard deviation) from an increase in teachers' problem-solving skills in technology-rich environments to the level of teachers from Australia



Note: Each bar displays the increase in student performance (expressed in % of standard deviation across all countries covered) in the respective field if teachers' problem-solving skills in technology-rich environments were raised to the level of Australian teachers (the highest performing teachers in the sample). Computations are based on the estimated coefficients for the relationship between teachers' skills in problem solving in technology-rich environments and students' scores in computer problem solving and computer mathematics, as explained in Box 2. The international standard deviation is the mean value of the country-level standard deviations (of student scores) for countries included in the sample in each field (computer problem solving and computer mathematics). It is equal to 96.05 PISA points for computer problem solving and to 89.28 PISA points for computer mathematics. The computer-based assessment of mathematics was offered as an option to countries in PISA (2012): the Czech Republic, Finland, the Netherlands and the United Kingdom do not have data on student performance in computer mathematics. The empirical analysis is based on the methodology of (Hanushek, Piopiunik and Wiederhold, 2014[57]) and is detailed in Box 5.3. In the Survey of Adult Skills (PIAAC): data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly. Also, in the Survey of Adult Skills (PIAAC): Chile, Israel, Singapore and Slovenia- year of reference 2015; all other countries- year of reference 2012.

Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and OECD (2012[9]), *PISA database 2012*, www.oecd.org/pisa/pisaproducts/pisa2012database-downloadabledata.htm.

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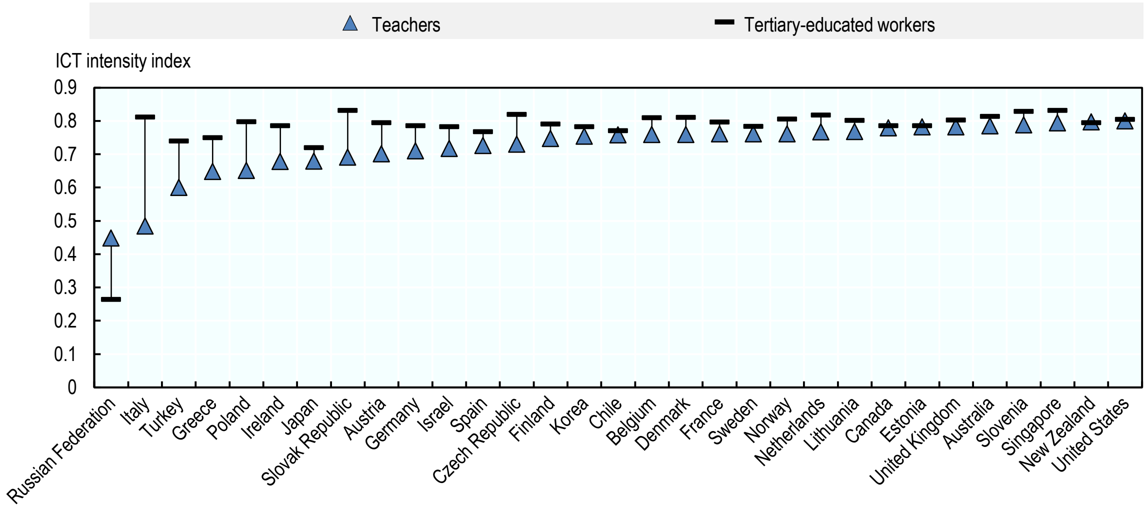
Figure 5.14. ICT intensity at work of the teaching profession

Median intensity of ICT use at work for teachers and workers with a tertiary education, by country



Note: Teachers and tertiary-educated workers are defined in Figure 5.12's note. The intensity of ICT use at work indicator is computed from the frequency with which workers perform a range of tasks using a computer and the Internet, such as reading and writing emails, or using software or a programming language (Grundke et al., 2017[62]). Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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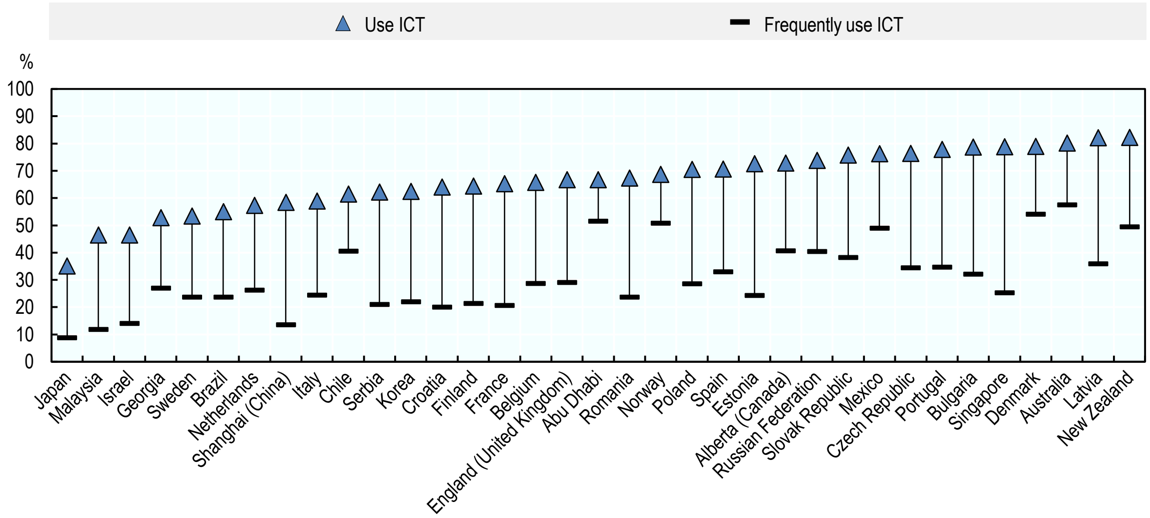
Figure 5.15. Teachers' use of ICTs in the class

Share of teachers using ICT for students' projects or class work, 2013



Note: Teachers who use ICTs are those who make any use of ICTs for students' projects or class work, either occasionally, frequently, in all or nearly all lessons. Teachers who frequently use ICTs are teachers who use ICTs for students' projects or class work frequently or in all/nearly all lessons.

Source: OECD calculations based on OECD (2013[52]), *TALIS database 2013*, http://www.oecd.org/education/school/talis-2013-results.htm.

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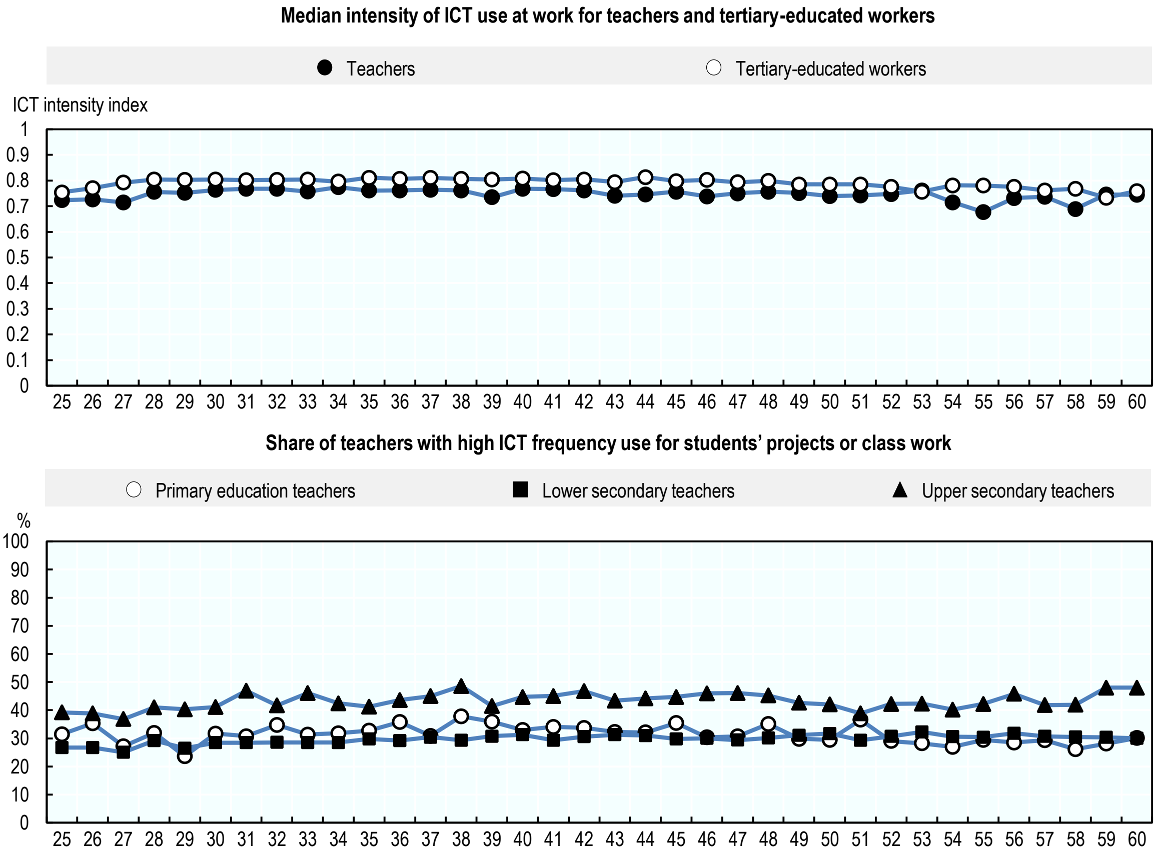
Teachers' demand for training may be greater because they are more ready and willing to learn in general, but many teachers specifically report needing professional development in ICT skills for teaching. Across OECD countries participating in TALIS, around 1 in 5 teachers indicate having a high level of need for such training (Figure 5.18). Together with professional development for teaching students with special needs, training in ICT skills for teaching is the most needed type of professional development reported by teachers in TALIS. At the same time, professional development programmes that focus on ICT translate into additional workload for teachers, since training is often provided outside of school hours. Training options need to be flexible and account for the potential impact such programmes might have on teachers' well-being.

Figure 5.16. Teachers' intensity of ICT use at work and as part of their classes, by age



Note: For the top panel: the intensity of ICT use at work indicator is defined in the note of Figure 5.14. For the bottom panel: high ICT frequency use occurs when ICTs are used frequently or nearly in all lessons for students' class work or projects. The sample for lower secondary teachers includes teachers from: Abu Dhabi (United Arab Emirates), Alberta (Canada), Australia, Brazil, Bulgaria, Chile, Croatia, Czech Republic, Denmark, England (United Kingdom), Estonia, Finland, Flanders (Belgium), France, Georgia, Israel, Italy, Japan, Korea, Latvia, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russian Federation, Serbia, Shanghai (China), Singapore, Slovak Republic, Spain, Sweden and United States. The sample for primary education teachers includes teachers from: Denmark, Finland, Flanders (Belgium), Mexico, Norway and Poland. The sample for upper secondary teachers includes teachers from: Abu Dhabi (United Arab Emirates), Australia, Denmark, Finland, Italy, Mexico, Norway, Poland and Singapore. Weights have been rescaled in data for both panels, so that each country contributes equally to the statistics.

Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis for top panel and OECD (2013[52]), *TALIS database 2013*, http://www.oecd.org/education/school/talis-2013-results.htm for the bottom panel.

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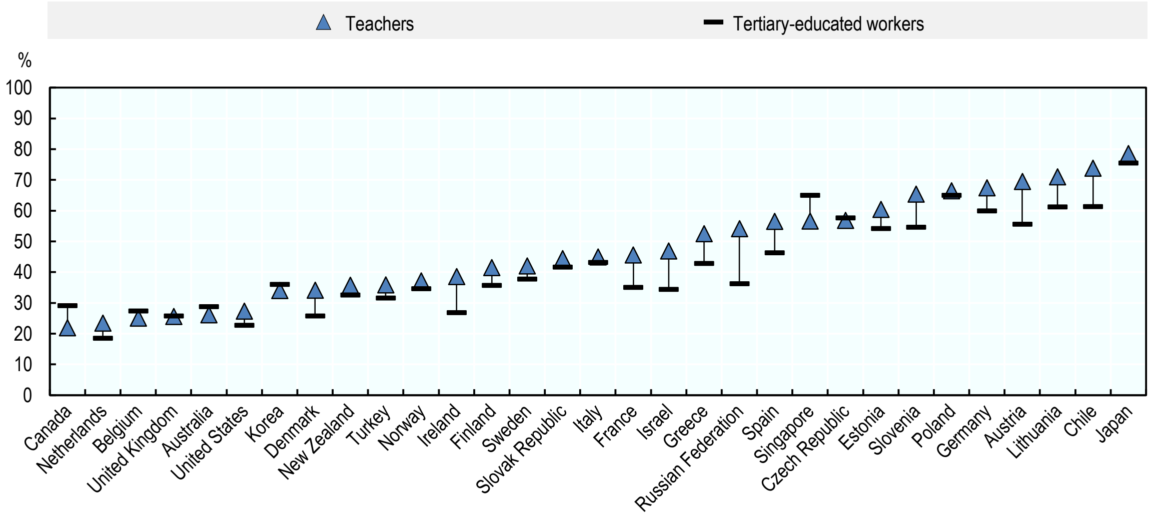
Figure 5.17. Share of teachers and non-teachers reporting needing training

Share of teachers and workers with a tertiary education reporting needing further training to do their job, by country



Note: Share of workers answering “Yes” to the question “Do you feel you need further training in order to cope well with your present duties?”. Teachers and non-teachers are defined based on the population of adults aged 25-65 years old. Teachers are adults self-reporting working in the following two-digit occupations as classified by the International Standard Classification of Occupations (ISCO-08): Teaching Professionals (ISCO 23). Non-teachers are all adults in employment with a tertiary education as defined by 1997 International Standard Classification of Education (ISCED): Tertiary (ISCED 5B, 5A, 5A/6). Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.
Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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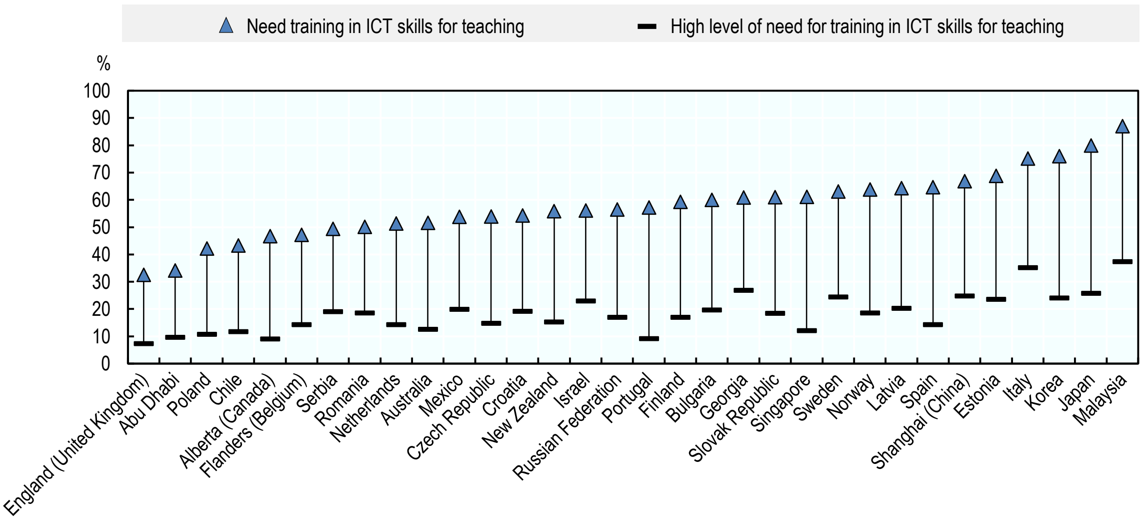
The teaching population is getting older, particularly at higher levels of education, while technology is increasingly entering schools and universities, which may partly explain why training needs are high (OECD, 2017[63]). On average across OECD countries, 37% of primary to secondary teachers were at least 50 years old in 2015, up from 31% in 2005. At the same time, the teaching profession is increasingly unattractive to students. Teachers’ salaries are lower than those of other, similarly educated full-time workers. Making the teaching profession attractive to students and developing high quality training for teachers, both initial and continuous, are important steps to ensure education systems adapt to new needs.

Figure 5.18. Share of teachers needing training in ICT skills for teaching

Share of teachers, by training need



Note: Teachers who need training in ICT skills for teachers are teachers who report any need for professional development in ICT skills for teaching, whether low, moderate or high.
Source: OECD (2013[52]), *TALIS database 2013*, http://www.oecd.org/education/school/talis-2013-results.htm.

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Learning in higher education and throughout life: The role of open education

The digital transformation is playing a major role in opening up higher education and knowledge to more students and to a broader range of socio-economic groups (Vincent-Lancrin, 2016[64]). Open universities, initially designed to serve older students, provide distance education to students who do not necessarily have an upper secondary education degree. Anybody can easily access for free an increasing amount of learning materials such as text, images, video and games. In recent years, massive open online courses (MOOCs) have developed. They enable anyone at any age to take a course provided by top universities, the business sector or independent experts.

The potential of open education for lifelong learning

People have to keep learning as the skills required on the job change. The question is whether and how open education, including MOOCs, can become a cornerstone of lifelong learning. Ideally, open education could not only help workers adapt their skills mix and knowledge to evolving labour market needs but also enable those who have left education without an appropriate level of skills to catch up with labour market needs. For this to happen, open education needs to: i) be adopted broadly by employers, workers and individuals; ii) benefit all individuals, and iii) provide high-quality learning material aligned with labour market needs.

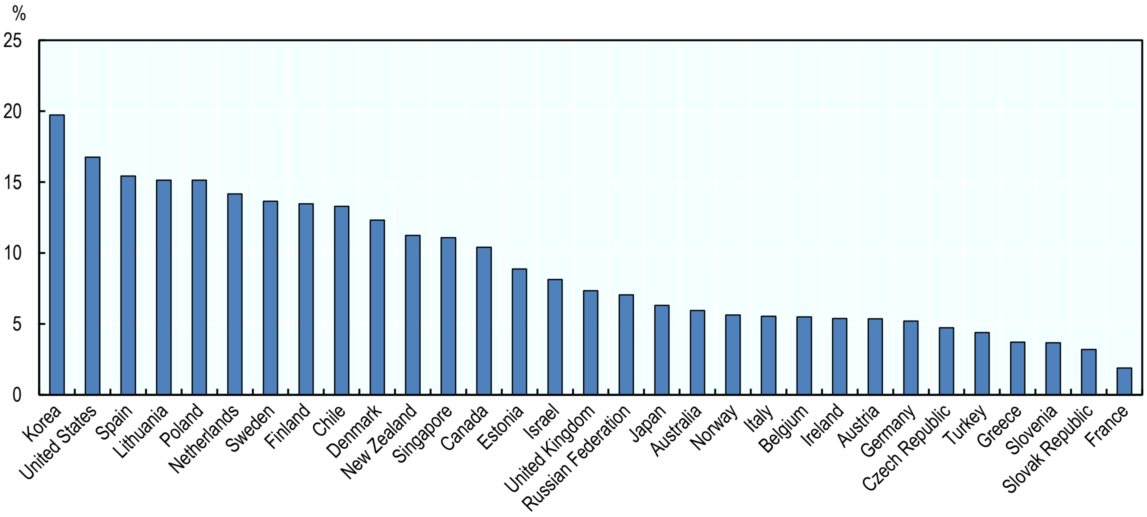
Open education courses, and MOOCs in particular, are often presented as a way to improve access to higher education across socio-economic groups as they are offered for free or at a low cost. However, if high-skilled people from the most advantaged socio-economic groups participate the most in open education, this may reinforce rather than diminish inequalities in participation in education and training.

The Survey of Adult Skills includes questions on participation in courses conducted through open or distance education that do not lead to formal qualification. This covers courses "which are similar to face-to-face courses but take place via postal or correspondence or electronic media, linking together instructors, teachers and tutors or students who are not together in the classroom". Since most countries were surveyed in 2012, when MOOCs were in their infancy, it is likely that responses mainly capture more traditional forms of open education such as courses or other material available online to learners.

Among countries covered by the Survey of Adult Skills in 2012 or 2015, 10% of the population participated in open education on average, but participation varied a lot, from almost 20% in Korea, a country with a lengthy and considerable experience with open education, to less than 2% in France (Figure 5.19). In most countries, young people are more likely to participate in open education than older adults but in Canada, Denmark, Finland and the United States, participation among prime-age adults is high (Figure 5.20).

Figure 5.19. Participation in open education

Percentage of the population having participated in open or distance education in the 12 months before the survey, 16- to 65-year-olds



Note: In the PIAAC questionnaire, open or distance education is defined as not leading to formal qualification. It covers courses that are similar to face-to-face courses but take place via postal or correspondence or electronic media, linking together instructors, teachers and tutors or students who are not together in the classroom. Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.
Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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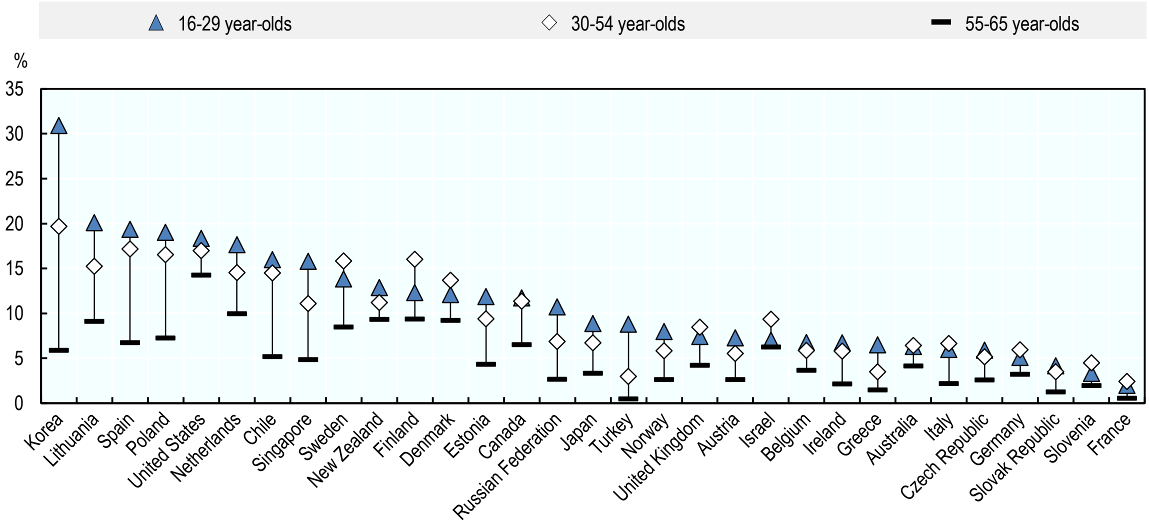
Figure 5.20. Participation in open education by age

Percentage of the population having participated in open or distance education in the 12 months before the survey, by age group



Note: In the PIAAC questionnaire, open or distance education is defined as not leading to formal qualification. It covers courses which are similar to face-to-face courses but take place via postal or correspondence or electronic media, linking together instructors, teachers and tutors or students who are not together in the classroom. Individuals aged 16 to 19 in formal compulsory education were not asked the questions. Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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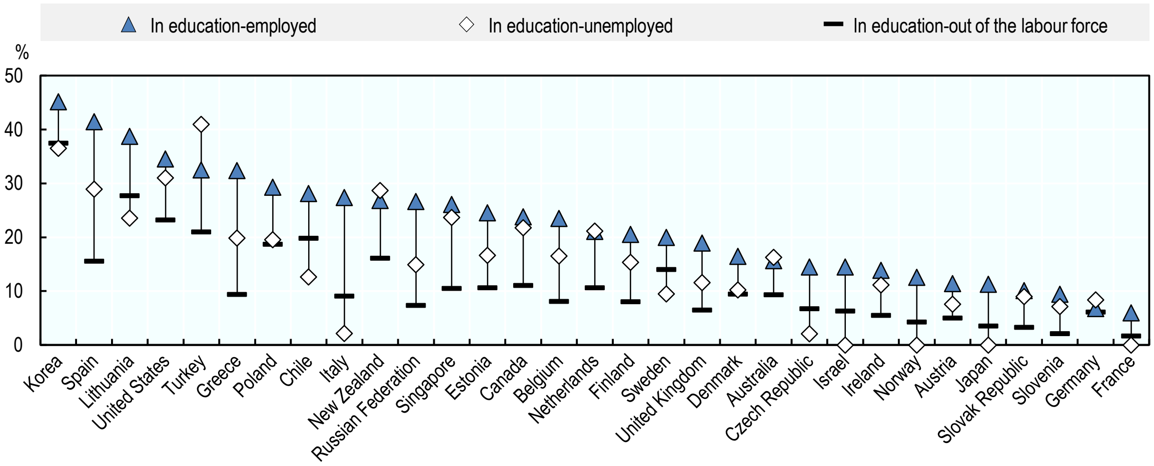
Open education offers flexible ways to learn. People already in formal education participate the most in open education. Among them, those who combine work and study, and to some extent, those in formal education who are looking for a job (unemployed) are more likely to participate than those who study but are out of the labour force (not looking for a job) (Figure 5.21). These results suggest that open education provides flexibility to people combining work and study and is used as a way to transition to the labour market. Among people who are not in education anymore, those who participate the most are also the employed, and to a lesser extent the unemployed. Open/distance education does not seem to be successful in reaching those out of the labour force who are not studying.

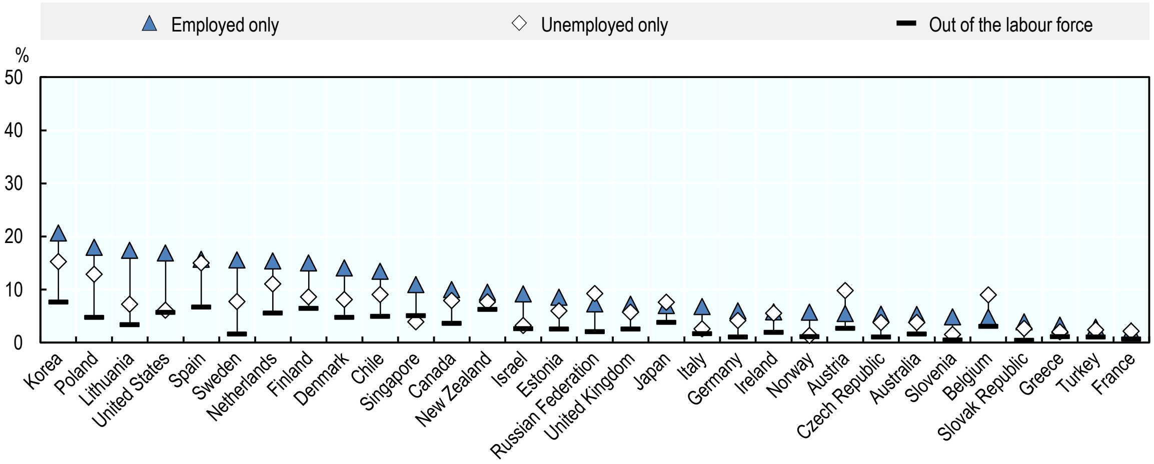
People participate in open/distance education mainly to improve job performance or prospects and to a lesser extent, to develop knowledge or skills more generally (Figure 5.22). Few participants aim to gain a certificate through their participation, perhaps because at the time of the survey, certificates were rarely attached to open education programmes. Another important reason may be that since most participants are in formal education, they aim to obtain a qualification through the formal education programme, not through participation in open education. More than 40% of participants find the experience very useful.

Figure 5.21. Participation in open education by employment and education status

Share of students having participated in distance/open education in the last 12 months prior to the survey



Share of non-students having participated in distance/open education in the last 12 months prior to the survey



Note: In the PIAAC questionnaire, open or distance education is defined as not leading to formal qualification. It covers courses that are similar to face-to-face courses but take place via postal or correspondence or electronic media, linking together instructors, teachers and tutors or students who are not together in the classroom. The first panel considers the share of individuals who declare to be in formal education and have participated in open/distance education; the second panel, those who declare not to be in formal education and have participated in open/distance education. Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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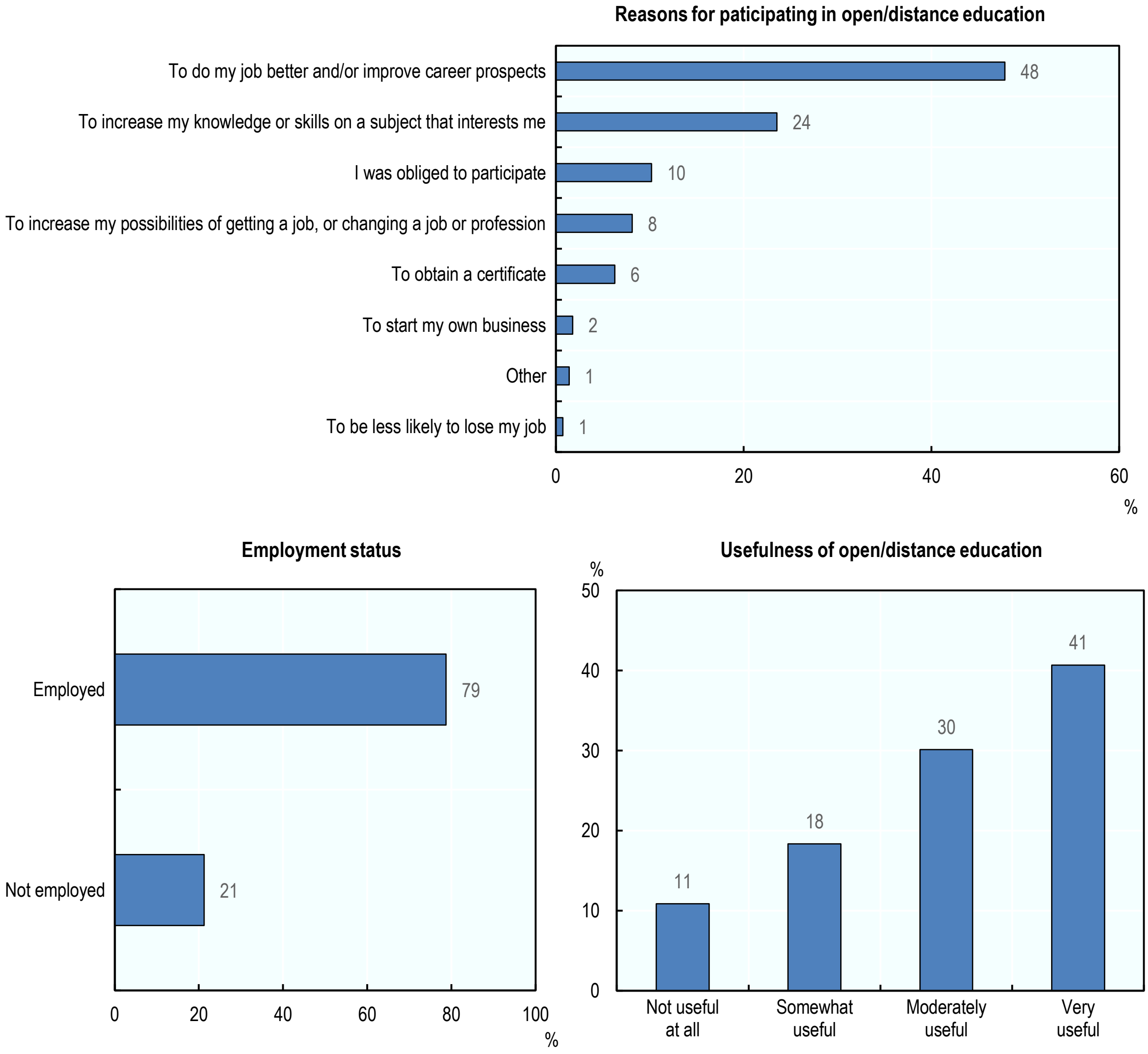
Figure 5.22. Reasons for and usefulness of participation in open/distance education

For individuals who have participated in distance/open education in the 12 months before the survey



Note: In the PIAAC questionnaire, open or distance education is defined as not leading to formal qualification. It covers courses that are similar to face-to-face courses but take place via postal or correspondence or electronic media, linking together instructors, teachers and tutors or students who are not together in the classroom.
Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Online delivery of education and training can also provide large geographic and time flexibility for learners to pursue education. Some examples of formal education programmes suggest that online delivery may expand the number of people pursuing education (Goodman, Melkers and Pallais, 2018[65]). The Georgia Institute of Technology's online master's degree in Computer Science, introduced in 2014, enables mid-career individuals who would not otherwise pursue education to obtain a degree. This programme is offered online at a significantly lower cost than in-person for a degree that is not signalled as having been obtained on line and is fully equivalent to the in-person degree. The online courses are versions of the same courses students take in person, designed by the same faculty, and graded using the same standards. In the first year, the course was taken by mid-career individuals whose average age was 34, compared with an average of 24 for in-person students.

One of the promises of open education is to expand access to tertiary education for disadvantaged students by lowering costs of delivery. However, as for other types of training, highly skilled and educated people are more likely to participate in open education (Figure 5.23). Hence, open education may tend to reinforce rather than close the gap in participation in adult education between low-skilled and high-skilled individuals. This is not surprising as most of these programmes are at a tertiary education level. Moreover, skilled and more privileged individuals have better access to the technology itself and to the enabling conditions – the time, the skills, and the motivation. Nonetheless, around 20% of the population without a tertiary degree had participated in open education at the time of the survey.

Recent opportunities brought by MOOCs

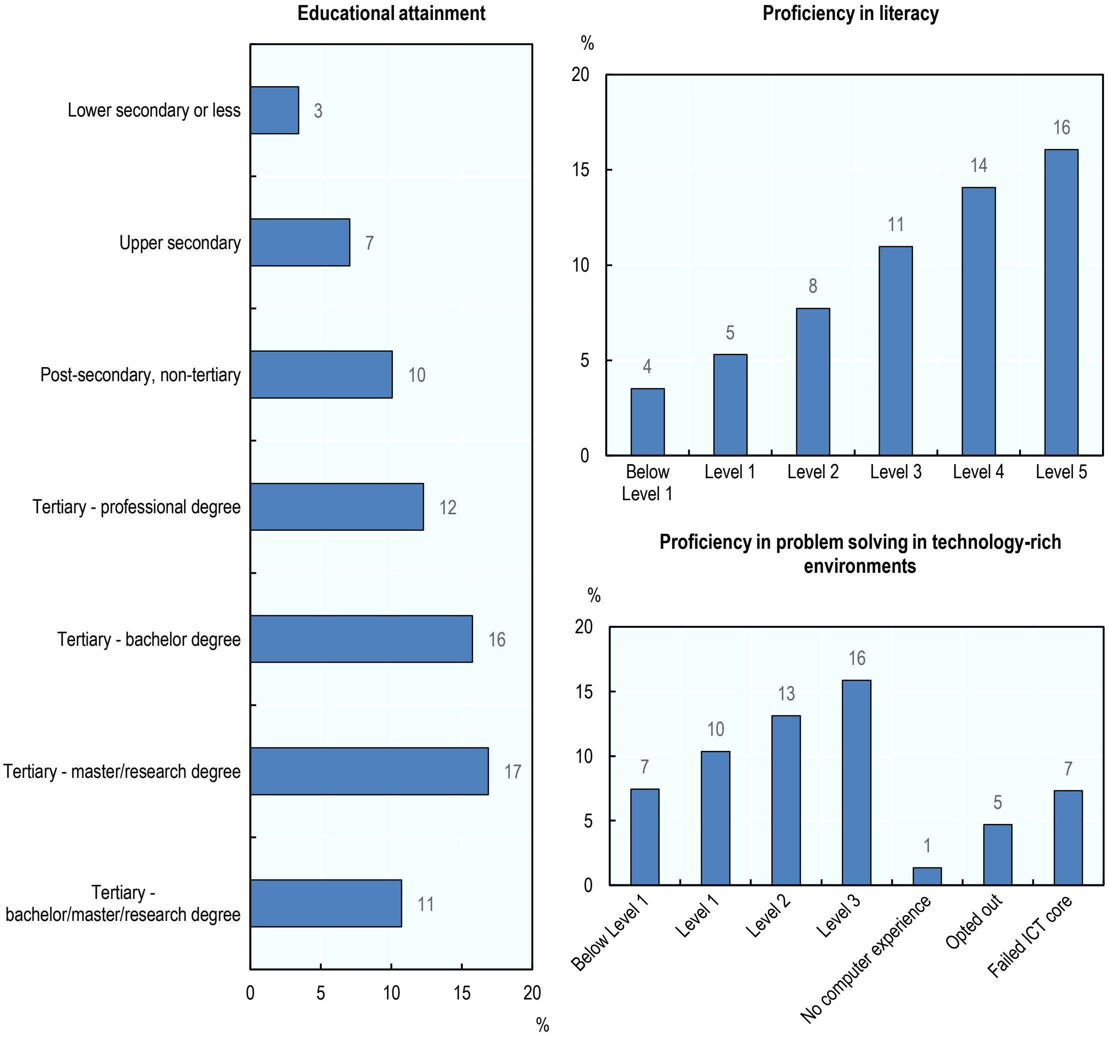
The recent development of MOOCs has boosted open education. Courses are generally provided by universities, including many top ones, but the business sector and independent experts also propose some MOOCs. Participation is generally free, but learners now have to pay to get a certificate. Contrary to traditional support provided online, participants in a MOOC take the course at the same period of time and can communicate with other participants through course forums.

In theory, MOOCs can help reduce the skills gap that has emerged as the digital transformation has changed skills needs (Music, 2016[66]). Learners can access courses from top universities in multiple fields with a large choice of when and what to learn. Such flexibility facilitates participation by various groups: the employed, those living in remote areas, and those who cannot afford to return to formal education. It also helps those who combine work and study to complete programmes by allowing them to complement regular courses with other courses. Learners can expand professional and personal networks around the world by participating in discussion forums. Such interactions and exchanges are increasingly needed in a globalised and digital world. Overall, MOOCs have the potential to better align education with employers' needs.

Due to data limitations, it has not been possible so far to get a broad view of the quality of MOOCs, and their impact on skills development and on equality in access to and participation in education. In particular, there are no data covering a large numbers of participants that show how MOOCs affect their skills and knowledge development. Some data on MOOCs proposed by the MIT and Harvard University covering 290 courses and 4.5 million participants between 2012 and 2016 give some indication on how MOOCs are used and by whom (Chuang and Ho, 2016[67]).

Figure 5.23. Participation in open/distance education by educational attainment and skills proficiency

As a percentage of each category



Note: In the PIAAC questionnaire, open or distance education is defined as not leading to formal qualification. It covers courses that are similar to face-to-face courses but take place via postal or correspondence or electronic media, linking together instructors, teachers and tutors or students who are not together in the classroom.
The figure shows that among adults with a tertiary master's or research degree, 17% have participated in open or distance education in the last 12 months prior to the survey.
Sources: OECD calculations based on OECD (2012[55]) and OECD (2015[56]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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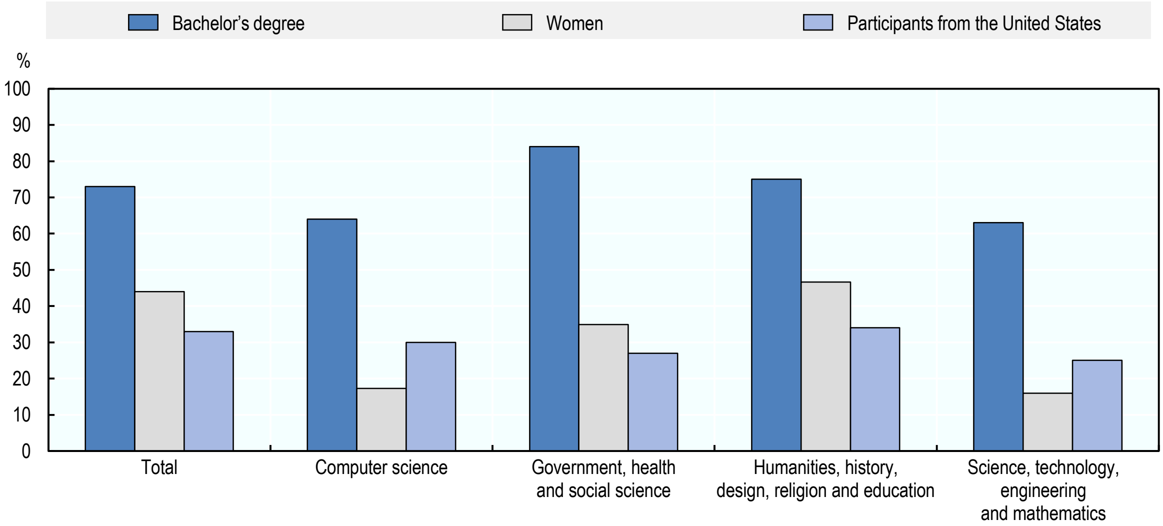
These data suggest that most participants in MOOCs are highly educated, with a bachelor's degree, confirming results on early phases of open education coming from the Survey of Adult Skills (Figure 5.24). Women are less likely to participate in MOOCs than men, for all disciplines covered in the sample. Participants from the United States do not represent the majority of learners, suggesting that MOOCs are efficient in breaking geographical frontiers. Forty percent of participants live in developing countries and among those who complete courses, participants in developing countries were more likely to report career or educational benefits (Zhenghao et al., 2015[68]).

Figure 5.24. Characteristics of participants in MOOCs, for a sample of MOOCs

Average characteristics of participants in a MOOC, by field of study



Note: Data cover 4.5 million participants in 290 courses provided by HarvardX and MITx between 2012 and 2016. The figure shows the median of the share of participants with a given characteristics (bachelor degree, women, from USA) over all MOOCs in the same field of study.
Source: OECD calculations based on Chuang, I. and A. Ho (2016[67]), "HarvardX and MITx: Four years of open online courses - Fall 2012-Summer 2016", http://dx.doi.org/10.2139/ssrn.2889436.

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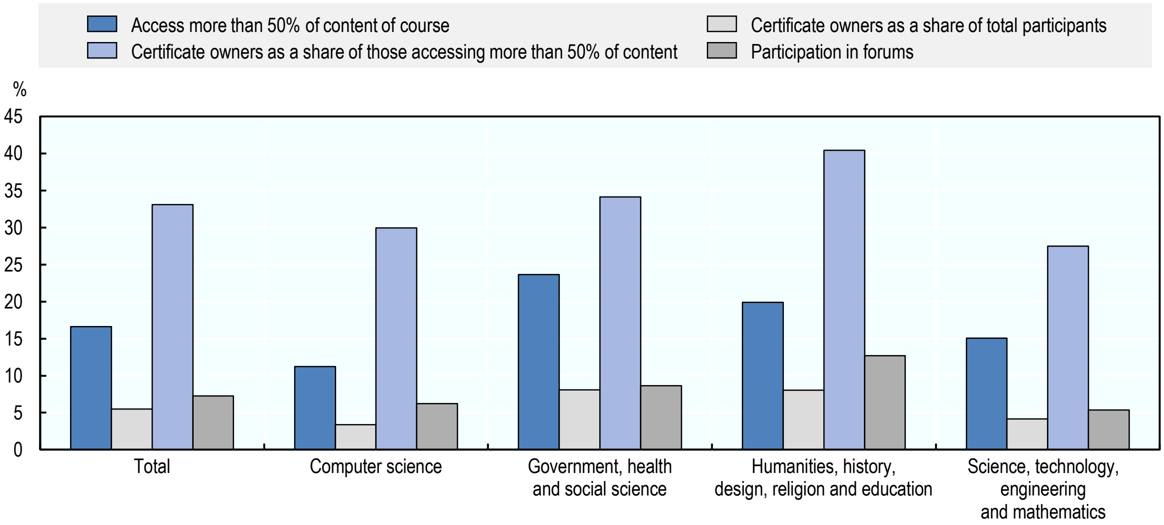
Data on this limited sample of MOOCs show that most participants access less than 50% of the content of the course and do not earn a certificate (Figure 5.25). When considering only engaged participants who look at more than 50% of the content of the course, the certification rate increases to 30%. Participation in MOOCs is less intense in computer sciences or science, technology, engineering and mathematics than in the humanities and social sciences, perhaps because of the higher degree of specialisation of the former. Participation in forums ranges from 5% to 12% of participants, on average, depending on the field of study.

Completion rates of MOOCs are low. This has often been put forward as one of their main limits, but participants in MOOCs have different learning goals. Some want to learn about a topic without intending to complete the course. Others would like their participation to be recognised by employers or education institutions as some form of extra education.

Figure 5.25. Patterns of participation in a sample of MOOCs



Note: Data cover 4.5 million participants in 290 courses provided by HarvardX and MITx between 2012 and 2016.
Source: OECD calculations based on Chuang, I. and A. Ho (2016[67]), "HarvardX and MITx: Four years of open online courses - Fall 2012-Summer 2016", http://dx.doi.org/10.2139/ssrn.2889436.

StatLink https://doi.org/10.1787/888933974577

A case study on the MOOC "Big Data in Education" delivered via Coursera suggests that completers and non-completers differ by their objectives but not by their readiness to learn (Wang and Baker, 2015[69]). Non-completers are more likely than completers to take the course because they are curious to take an online course, they use it as a supplement or complement to other courses, or they cannot afford to pursue formal education. A range of questions aiming to capture participants' goal orientation and readiness to learn show no significant difference between completers and non-completers. Another study finds that many participants who may be classified as non-completers are in fact still participating in the course in their own preferred way, either at a slower pace or with a selective approach to the material of the course engagement (Onah, Sinclair and Boyatt, 2014[70]).

More data are needed to understand how and what participants in MOOCs learn, both completers and non-completers. For MOOC providers, the diversity of objectives and backgrounds of participants makes it difficult to develop MOOCs that are appropriate for all learners.

The ranking of MOOCs according to their popularity gives an indication of what participants try to learn. Most popular courses are in computer sciences but also in social and emotional skills development and traditional topics such as finance and English (Box 4.1). The popularity of courses to develop social and emotional skills such as the MOOC "Learning how to learn: Powerful mental tools to help you master tough subjects", which has attracted more than 1 million participants (Class Central, 2017[71]), suggests that participants in MOOCs worry about their capacity to learn and adapt their skills to changing requirements.

Box 5.4. Most popular MOOCs as of 2017

Based on statistics on185 MOOCs provided by Coursera and EdX, Class Central has ranked courses according to their enrolment number, considering all sessions of each MOOC as of 2017. The 15 most popular MOOCs according to this ranking are:

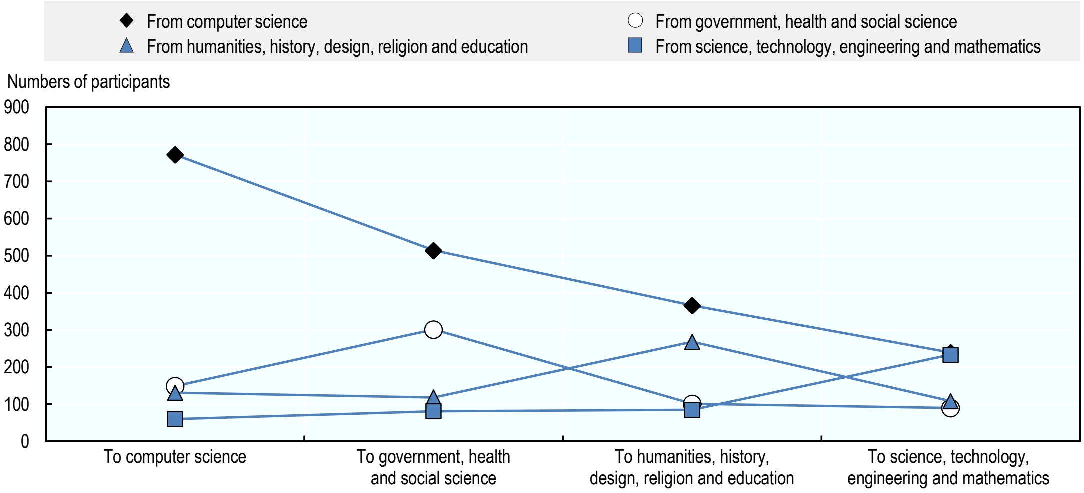
1. Learning How to Learn: Powerful mental tools to help you master tough subjects / University of California San Diego
2. Machine Learning: Master the Fundamentals / Stanford University
3. R Programming / Johns Hopkins University
4. Introduction to Finance / University of Michigan
5. The Data Scientist's Toolbox /Johns Hopkins University
6. Think Again: How to Reason and Argue / Duke University
7. Algorithms: Part 1 / Princeton University
8. Developing Innovative Ideas for New Companies: The First Step in Entrepreneurship / University of Maryland, College Park
9. Understanding IELTS: Techniques for English Language Tests / British Council
10. Programming Mobile Applications for Android Handheld Systems – Part 1 / University of Maryland
11. Cryptography I / Stanford University
12. Programming for Everybody (Getting Started with Python) / University of Michigan
13. Social Psychology / Wesleyan University
14. Introduction to Public Speaking / University of Washington
15. Model Thinking / University of Michigan

Source: Class Central (2017[71]), *The 50 Most Popular MOOCs of All Time*, https://www.onlinecoursereport.com/the-50-most-popular-moocs-of-all-time/ (accessed on 20 February 2018).

MOOCs can break down the boundaries between knowledge areas and help develop multidisciplinarity. When learners enter a MOOC platform, they may be tempted to start other courses in other disciplines, which can be done more easily than at universities on site. Data on MOOCs from Harvard University and the MIT show that multiple enrolments are frequent (Chuang and Ho, 2016[67]). Many participants start with courses in computer science and continue with courses in other subjects, such as government, health and social science (Figure 5.26).

Figure 5.26. Multiple enrolments in MOOCs

Average multiple enrolments per course, by subject and previous course subject



Note: Data cover 4.5 million participants in 290 courses provided by HarvardX and MITx between 2012 and 2016. The graph shows that on average among participants in a MOOC in computer science, 772 have participated in another course in the same area and 514 have participated in a MOOC in government, health and social sciences.

Source: OECD calculations based on Chuang, I. and A. Ho (2016[67]), "HarvardX and MITx: Four years of open online courses - Fall 2012-Summer 2016", http://dx.doi.org/10.2139/ssrn.2889436.

StatLink https://doi.org/10.1787/888933974596

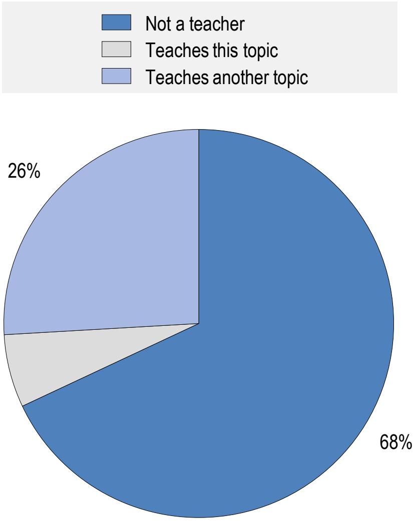
MOOCs can provide simple, flexible and low-cost options for companies to train their workers. Employers can simply encourage or allow their workers to take a course on their working time. Given the wide range of courses, employers in many industries could adopt this option. Examples of use of MOOCs by employers mostly concern large firms, some of which have developed their own content on topics such as management, computer science and finance (Hamori, 2018[72]). However, most MOOCs proposed by universities may be too general to meet the needs of firms. Many MOOC platform providers have started exploring MOOCs for professional development and there are already some successful examples of MOOCs in this area (Music, 2016[66]). When employers take part in the design of a MOOC, they can use this experience to attract new employees.

In general, however, firms have not fully used the potential of MOOCs to develop their employees' skills. A reason might be the lack of information and the organisation of the provision of training (Hamori, 2018[72]). Employers may not consider MOOCs as a substitute to other forms of training. Line managers, who know the domain of expertise, are well placed to initiate this type of training and manage workloads to enable workers undertake courses. Human resources managers, who are in charge of training policies, are less likely to do so. For workers, it is easier to look for MOOCs and try them out if they think this is going to be valued by employers. Human resources managers and employers could help employees choose MOOCs by looking at the quality of providers, whether courses have a clear description, and learning outcomes. As MOOCs and open education mostly seem to attract people who are already employed, governments could try to foster the use of MOOCs by employers as a way to develop adult learning. They could raise employers' awareness of the potential of MOOCs and help them partner with MOOC platforms to find or develop courses aligned with their firms' skills needs.

MOOCs also help diffuse knowledge that can be used by the teaching profession, either as material to improve their own courses or as a pedagogical tool. Many MOOC participants are teachers (Seaton et al., 2014[73]). In the United States, some universities[2] have partnered with MOOC platforms to propose preparatory courses to high school students and teachers in Advanced Placement courses. These offer tertiary-level curricula and examinations to high school students; top-scoring participants may obtain placement in universities or course credit (Seaton, 2016[74]). Students using MOOCs rather than standard material tend to achieve slightly better results.

Figure 5.27. Teachers participating in MOOCs, for a sample of MOOCs

As a share of participants in the survey



Note: Data come from a survey item administered in 83 HarvardX and 101 MITx course.
Source: Seaton, D. (2016[74]), *Complementary Models of MOOC Instruction for Advanced Placement High School Courses*, https://blog.edx.org/complementary-models-mooc-instruction-advanced-placement-high-school-courses (accessed on 03 April 2018).

StatLink https://doi.org/10.1787/888933974615

MOOCs and open education can indirectly raise the quality of education and thereby ensure that students are better prepared for changing skills needs. MOOCs and open education may also increase competition between universities, but this depends on the quality of MOOCs, which remains to be better understood. Governments need more information on the quality of MOOCs before supporting their integration in the education system and adult learning. Up to now, the absence of pedagogical and technological standards and a lack of government expertise and reactivity on this subject have made this type of public investment risky (Music, 2016[66]). Adapting MOOCs to a larger group of participants – including those with few computer skills, few skills to know how to learn and little capacity to motivate themselves – remains another important challenge.

Recognising and certifying skills as sources for learning diversify

The way skills are recognised and certified needs to evolve as the learning environment and the world of work are affected by the digital transformation. As digitalisation of learning increases, more people are likely to acquire skills outside formal education. As a result, qualifications obtained through initial education may reflect less and less well the skills people have. At the same time, the digitalisation of the world of work is changing skills needs, so employers may need broader and more up-to-date information on workers' skills than standard qualifications can supply.

Rationale

The expansion of skills acquisition throughout life and through diverse sources, including open education and MOOCs, poses the question of how to formally recognise and certify these newly acquired skills. Technology enables people to develop skills through non-formal learning (structured classes that do not lead to a formal degree) and informal learning (learning that takes place as part of other activities) that are not always reflected in qualifications.

The need to ensure that qualifications better reflect skills is also being felt at universities, where the increasing share of students has been accompanied by more variability in the skills of young graduates (Paccagnella, 2016[75]).

In parallel, employers need different skills that are not reflected in most qualifications. More and more they are valuing social and emotional skills (Deming, 2017[76]). As technology makes knowledge and skills date more quickly, employers need workers with the capacity to learn and adapt to new tools and methods.

When part of the chain can be automated, the economic value of the remaining tasks performed by workers increases and poor performance greatly reduces the value of output (Autor, 2015[77]; OECD, 2017[78]). Hence, employers increasingly need clear signals about workers skills. When diplomas reliably reflect what workers can do, workers are more likely to be able to perform well the tasks for which they have been recruited. In addition, the world of work is increasingly global, requiring transparency and standardisation of skills and qualifications acquired abroad.

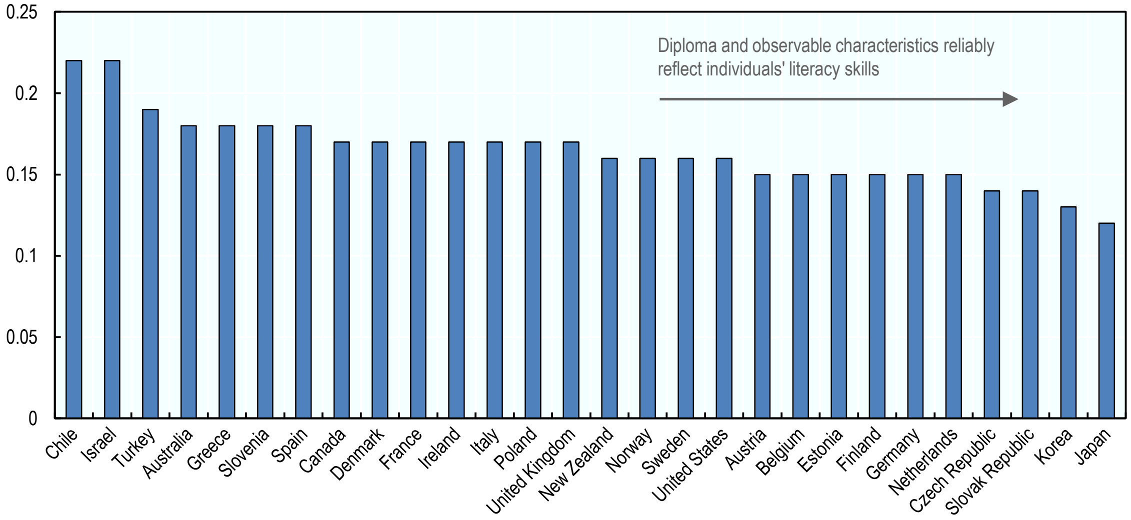
The Survey of Adult Skills (PIAAC) shows how countries differ in their skills dispersion, for instance in terms of literacy skills (OECD, 2017[78]). Some observable characteristics, such as the level of education, participation in training, age, and gender explain this dispersion. However, part of the dispersion cannot be explained by differences in observable characteristics; this is called the unobservable skills dispersion. In countries with high unobservable skills dispersion, employers face greater difficulties in recruiting individuals who perform at the level expected given their education level and other observable characteristics. An indicator based on the Survey of Adult Skills (PIAAC) shows that this dispersion is low in countries like the Czech Republic, Korea, Japan, and the Slovak Republic.

Policies

A better signalling of skills requires recognising and certifying: 1) skills acquired throughout life and therefore outside formal education, for instance skills acquired by learning on the job and those acquired through non-formal education such as MOOCs; 2) a broader range of skills than those included in standard diplomas, such as social and emotional skills.

Figure 5.28. Dispersion in unobservable component of literacy skills

Standard deviation of the unobserved component of literacy scores after accounting for education and other observable characteristics, by country



Note: The unobservable skills dispersion is computed by: 1) estimating a regression of the logarithm of literacy scores on education, age, gender, immigration background and training; 2) computing the residuals of the regression for each individual (logarithm of literacy scores minus fitted values); 3) computing the standard deviation of the residuals by country. Chile, Greece, Israel, New Zealand, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.
Source: OECD (2017[78]), *OECD Skills Outlook 2017: Skills and Global Value Chains*, http://dx.doi.org/10.1787/9789264273351-en, Table 3.2.

StatLink https://doi.org/10.1787/888933974634

There are two major non-exclusive approaches for certifying a broader range of skills acquired throughout life. The first approach consists in facilitating the recognition of skills acquired outside formal education, such as through learning on the job, within the formal qualification framework. For instance, in recognition of pre-existing skills, the duration of a formal education and training programme can be reduced, or a person can obtain direct access to the final qualifying examination. This approach exists in many countries and is well-suited to recognising and certifying specific skills acquired through work-based learning, such as through apprenticeship (Kis, 2018[79]). This approach leads to a real assessment of skills and could therefore be expected to be fully recognised by employers. Expanding this approach would be costly, however, for learners and for education and training institutions. Apart from those in regulated occupations, most learners would not always need the additional qualification for their career progression. Finally, while this approach can help in certifying skills acquired throughout life, it is unlikely to lead to the recognition of a broader range of skills than those already recognised in qualifications.

The second approach for certifying a broader range of skills acquired throughout life consists in developing certification of skills acquired through non-formal or informal learning as a complement to formal qualification. Digitalisation has boosted skills certification through the emergence of open badges and credentialing platforms (Box 5.5). In addition to enabling certification of skills acquired throughout life, these programmes aim to signal a broader range of skills than qualifications do, including not only professional and technical skills but also social and emotional skills, such as leadership qualities.

At the moment, certification mechanisms rely on proof of participation in learning activities, work experience or other types of activities but do not test the skills of individuals. For certificates of non-formal and informal learning to a play a bigger role in education and work trajectories, such certification would need to be based on valid and reliable assessments.

As sources for learning diversify and lifelong learning becomes increasingly important, it will become crucial to separate the assessment of skills from the provision of education and training. Some large firms, including in the ICT industry, test skills on their own and rely less on diplomas. However, this approach is not suited to all firms and all occupations. Assessing practical technical skills directly, in an authentic working environment, can be very costly because of the material and equipment involved (Kis, 2018[79]). Technology may enable cheaper ways of assessing practical skills. Apart from providers of formal education and training, however, no institutions have proved yet that they have the capacity to develop reliable assessments of skills on a large scale.

Box 5.5. Online certificates, badges and portfolios

Online certification has proliferated over the last years. Open badges, introduced in 2011 by the Mozilla Foundation, aim to recognise skills from various activities, especially those developed outside formal education. They are issued through an open badges platform by education and training providers, employers and many other organisations that propose non-formal and informal learning. Badges may enable individuals to present their skills in a more flexible way than full qualifications, or to signal specific interests or knowledge.

In the United States, several large firms have adopted open badges, including IBM, Microsoft and Oracle (Fong, Janzow and Peck, 2016[79]). ACE CREDIT, the US organisation in charge of validating non-formal and informal learning, has partnered with Credly, an open badges platform, to enable education and training providers, employers, and other participants to issue open badges.

Outside the United States, RMIT University in Melbourne is also working with Credly to issue badges for skills that firms value and that are not tested in exams.

Some platforms propose direct certification of skills, in which certificates are issued on the request of individuals. Degreed, launched in 2012, proposes the certification of more than 1 500 skills. The site validates work experience and other learning events and breaks down these learning experiences into skills categories. Validation is based on the firm's expertise and does not involve exams or tests.

Students, workers and job seekers often share the open badges and digital certificates they have acquired on social media platforms like LinkedIn, Facebook and Twitter. LinkedIn is also an example of online portfolios that have developed in parallel with online certification. While portfolios do not certify skills, workers use them to showcase their experience and signal their skills to employers, who may use this information in the recruitment process.

Source: Fong, J., P. Janzow and K. Peck (2016[79]), "Demographic Shifts in Educational Demand and the Rise of Alternative Credentials", https://upcea.edu/wp-content/uploads/2017/05/Demographic-Shifts-in-Educational-Demand-and-the-Rise-of-Alternative-Credentials.pdf (accessed on 16 April 2018).

Recognising skills acquired through open education poses a particular challenge, especially in the case of MOOCs, as they resemble formal education. Most open education and MOOC learners already have a tertiary degree. For these participants, obtaining an additional certification may be less important than evidence of participation in a learning or skill acquisition activity (Figure 5.21). For high-school or university students, however, it might be important to gain credits that are recognised within the formal education system.

MOOCs have already moved a long way towards certification. Most MOOCs lead to a certificate issued by MOOC platforms or jointly by the MOOC platform and the provider, such as open badges or other types of digital badges. Recently, MOOC platforms have developed "nanodegrees" (Udacity), "micromasters" (edX) or "specialisations" (Coursera), comprised of a bundle of around five courses on a specific topic. They may constitute good skills signals for employers as they encapsulate a range of competences that are necessary for that specific discipline. In addition, they can sometimes enable students to apply for an accelerated on-site programme.[3]

In most cases, certificates earned through MOOCs are not understood as part of larger qualifications. In the United States, however, ACE CREDIT, the organisation in charge of validating non-formal and informal learning (part of the American Council on Education), has included MOOC certificates in its credit recognition programme, although only a small number of MOOCs have been certified so far (Box 5.5). Higher education institutions and employers can use recommendations from this organisation to make their validation decisions. Some institutions in Europe offer formal accreditation in terms of the European credit transfer and accumulation system but accumulation of these credits does not entail the award of a degree.

Assessing what someone has learned from a MOOC requires making sure that the person who takes the test is the one who took the online course. In 2013, Coursera launched a verified certificate system that considers the typing pattern of the students to link them to their ID and deliver a nominative course completion certificate. Half of the courses offered by Coursera were eligible for this type of certificate in 2016.

Improving recognition and certification of skills to respond to employers' changing needs and evolving ways of learning requires strong co-operation between governments (including national accreditation agencies), education and training providers, and employers. Options to better recognise and certify skills include:

- Moving to a competencies-based approach to formal qualification, to improve transparency and homogeneity of diplomas issued by different education institutions. A competencies-based approach has developed over the last decades in higher education (Nodine, 2016[80]). Participation of employers in the design and review of qualification frameworks is important to ensure the qualifications are recognised.
- Encouraging the development of certificates for skills acquired through non-formal and informal learning. In parallel, governments, education and training providers, and employers can co-operate to define standards and good practices for certification, to move towards a more reliable assessment of the skills people really have.

- Integrating certificates earned through non-formal and informal learning in national qualification frameworks. This would need to be done on a case by case basis, respecting all relevant standards, to secure the trust of employers and education providers. Whether certificates can lead to credits or other routes to a formal qualification would be for education providers to decide.
- Governments can work together to harmonise recognition and certification of skills practices at an international level.

Summary

The digital transformation offers many new sources and forms of learning in schools, in jobs and at home. However, the benefits of these new forms of learning cannot be taken for granted.

In schools, technology needs to be carefully integrated so that it amplifies teaching and learning. Teachers need to be trained to use technology to improve teaching practices and students' results. Technology can enable more individualised teaching, in which students can progress at their own pace. Instead of spending a large amount of time delivering traditional classes, teachers can devote more time to teaching complex skills, such as critical thinking and team work, and have a computer provide routine information. In practice, few countries seem to have realised the potential of technology as a teaching and learning asset on a large scale. As well as learning via technology at school, students need to learn about technology, including digital skills, such as browsing safely and effectively on the Internet, computational thinking, and digital critical thinking. Countries need to adopt strategies for introducing technology in schools that go beyond quantitative aspects such as the number of tablets per children.

Training teachers to help them make the most of technology at school is crucial. Students from various OECD countries face the same needs in digital skills, but there are large variations among countries in teachers' problem-solving skills in technology-rich environments.

Countries need to assess regularly the effect of technology in schools to make sure that it helps and does not hinder students' learning. As technology evolves, the way students make use of it and the time they devote to it keep on changing. The development of the use of smartphone and chatting in schools is a good example of these changes.

Policies on the integration of technology need to be adjusted regularly to make the most of the positive effects while limiting negative ones.

Outside schools, technology also offers potential for learning via open distance resources, particularly MOOCs. However, these new learning opportunities are mostly benefiting highly skilled people, even though they are accessible to everybody. Governments can co-operate with education and training providers, employers, job-search agencies and social policy institutions to realise the full potential of open education as a universal learning tool.

Notes

[1] Between 2009 and 2015, the largest drops in students' use of ICT infrastructure available in schools were observed in Denmark (25 percentage points) and Poland (20 percentage points). In Denmark, more than 80% of students at grade 11 reported using their own laptops in class for learning at least once per week (European Commission, 2013[49]).

[2] In 2015, Davidson College in the United States launched a series of online test preparation modules through the MOOC provider edX for high school students and teachers in Advanced Placement courses.

[3] For instance, learners who pass an integrated set of MITx graduate-level courses on edX.org, and one or more proctored exams, will earn a MicroMasters credential from MITx, and can then apply for an accelerated on-campus master's degree programme at MIT or other top universities.

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Chapter 6. Policies to support lifelong and countrywide learning for a digital world

This chapter considers two policy objectives that have a key role to play in making the most of the digital transformation: fostering lifelong learning and ensuring geographical inequalities do not exacerbate. Lifelong learning is critical so that all workers and citizens can adapt to changes at work and changing societies. Strong lifelong learning systems rely on a combination of policies that provide high-quality education and training for all, anticipate changes in the demand of skills and ensure that education and training systems are well aligned with labour market needs. Policies are also needed that facilitate mutually reinforcing local benefits of skills and technology in order to prevent the magnification of regional differences. While different in nature, the need to foster lifelong learning and the need to prevent geographical inequality both require a comprehensive approach to the digital transformation that co-ordinates a range of policies and actors.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

New technologies profoundly change the world of work (as Chapter 2 showed) as well as societies (Chapter 4). To adapt to these changes, people need to be able to learn and adjust their skills set throughout life. Policies that facilitate and encourage lifelong learning for all are at the core of the policy response to the digital transformation and, in particular, the uncertainties it creates about future skills needs. Strong lifelong learning systems require a combination of targeted policies that ensure high quality education and training is accessible to everyone, at all stages of life and including all types of learning. Successful lifelong learning also relies crucially on policies and tools that anticipate skills required in the future and ensure that education and training systems are well aligned with labour market needs.

Policy makers also need to take into account the fact that digital transformation affects regions within countries differently. The digital transformation tends to exacerbate existing gaps between regions' skills endowments. A range of policies, centred on skills, is necessary to help lagging regions catch up and ensure that the benefits of digital transformation are shared equally within countries.

The need to foster lifelong learning and the need to offset the unequal geographical impact of the digital transformation are different in nature. But each requires a comprehensive approach to digital transformation and the co-ordination of a range of policies and actors. This co-ordinated policy effort goes beyond the need for specific skills policies that address changes in the world of work (discussed in Chapters 2 and 3) and in societies (discussed in Chapter 4), as well as policies that make the most of technology to foster learning inside and outside schools (Chapter 5).

This chapter first reviews policies that foster lifelong learning in an increasingly digitalised world. The second section examines the geographic dimension of digitalisation and policies that can help all regions benefit. The third section outlines a policy package that can help countries make the most of digitalisation and the co-ordination necessary to implement these policies.

The main findings from the chapter are:

Co-ordinating policies that foster lifelong learning for all

- Enabling life-long and life-wide learning for all is a crucial policy response to changing skills requirements and the uncertainty of future skills needs.
- Policies need to raise the quality of education and training opportunities throughout life. For initial education, this means adapting the school curriculum to changing skills requirements and training teachers to face these changes. For adult education and training, it is vital to ensure that programmes respond to labour market needs at the country and local levels, to set standards for non-formal education and training, and to assess it better.
- Policies need to make learning opportunities much more flexible and responsive to labour market needs through appropriate funding mechanisms, skills assessment information and effective career guidance.

Co-ordinating policies that offset the unequal geographical impact of digitalisation

- Digitalisation affects regions within countries differently, and exacerbates the existing gaps between regions' skill endowments. Technology-intensive firms and industries, and high-paying jobs, are drawn to regions with high-skilled workers. High-paying jobs further attract high-skilled workers.

- Skills-related policies can help lagging regions catch up. High-quality early childhood education is crucial to bridge skills gaps that can emerge at an early age between children of different socio-economic status and different geographic location. Disparities between regions in secondary students' performance also need to be addressed.
- High-quality higher education institutions can increase demand for and supply of high-skilled individuals when entrepreneurial ventures are located close to the cutting-edge research that they rely on. They also enable skilled individuals to be more mobile geographically, reducing unused productive capacity in declining areas and closing income gaps. However, higher education institutions are very unequally distributed within countries.
- A wide range of policies is necessary to help lagging regions catch up:
    - High-quality vocational education and training that has a strong work-based learning component and is aligned with local labour market needs can foster local development while raising young people's employability.
    - Distance-based financial aid, information policies, role models and mentoring can bridge the educational aspiration gap that separates students who are far from a university and those who live nearby.
    - Geographical labour mobility, which has been in decline in some OECD countries, needs to be improved to match job opportunities with workers' skills. This can be achieved by changing inefficient land use regulations, moderating the tax bias towards home ownership, revisiting and possibly harmonising local social transfers, and providing financial assistance to displaced workers in order to mitigate migration costs.
    - Investments in digital infrastructure are essential so that advanced technologies can be adopted and rural areas and remote territories can enjoy the benefits of digitalisation.

Co-ordinating policies across areas

- Digitalisation has wide-ranging effects on economies and societies and requires a package of co-ordinated policy responses that go beyond learning. These need to promote digitalisation where it increases productivity and well-being while cushioning its negative impacts.
    - Labour market policies and institutions that balance flexibility and worker protection, particularly for workers in non-traditional working arrangements, can facilitate mobility and the efficient allocation of workers to jobs and sectors. At the same time they can encourage high-performance work practices and ongoing learning.
    - Tax policies can offer incentives for undertaking and providing learning. Research and innovation policies can unlock the potential of digital technologies for economic and social well-being, while regional and local development policies can help spread the benefits of digitalisation.
    - Housing policies can enhance worker mobility, while migration policies can increase countries' attractiveness in the global competition for talent. Policies that support infrastructure, both physical and digital, are important to ensure that everyone has access to learning opportunities.

  - Social protection policies are vital to shield workers from the risks of digitalisation. They may need to evolve from a last resort to a broader safety net as a wider range of workers navigates more frequent and more complex work transitions.

- The geographical impact of digital transformation requires co-ordination of policies across levels of government. For instance, adult learning policies at the local level can be co-ordinated with regional development strategies.
- Several countries have put in place strategies to co-ordinate policy concerning the digital transformation. However, few of these strategies seem to have the necessary level of government engagement, breadth of policy coverage and concreteness of policy responses.

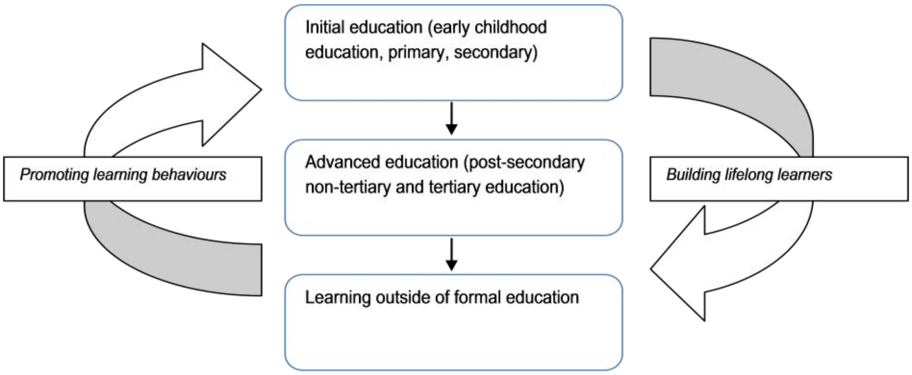
Fostering lifelong learning in a context of uncertainty

The rapid pace of change at work and in society brought about by digitalisation requires flexible learning systems that are both lifelong (accessible to all at any age) and life-wide (that promote and recognise learning acquired outside of formal education systems). Policies that favour such flexible systems are crucial to meet changing skills needs and manage the uncertainties surrounding these changes.

OECD countries have recognised for several decades the economic and social benefits of knowledge and skills for individuals and societies (OECD, 2001[1]; OECD, 2013[2]). In recent years, the focus has shifted to the necessity for individuals to maintain, improve and adjust their skills throughout life in response to globalisation and the digital transformation of the economy (IMF, 2017[3]; OECD, 2017[4]; OECD, 2017[5]).

Lifelong learning systems include all stages of education and learning, "from cradle to grave", within the formal education system and outside of it (OECD, 2001[1]). Such systems facilitate the mobility of learners between different levels and types of education and training, departing from a traditional conception of education as mainly formal and organised in successive levels without interaction between them (Figure 6.1).

Figure 6.1. Lifelong learning systems: Key features



Key conditions: accessibility, quality and equity of learning opportunities

Key policy levers: information, funding and governance

Countries have a highly diverse range of approaches to designing and implementing lifelong learning systems. These often depend on countries' institutional settings, such as the role of the government in funding and delivering education, and the level of engagement in education and training of social partners such as employers and trade unions (Saar and Ure, 2013[6]).

Rationale for supporting lifelong learning in a digital world

A high level of skills and a diversified skill set can help individuals be resilient in the digital economy. Workers in digitalised workplaces use a range of cognitive and non-cognitive skills more intensively than in non-digital workplaces (Chapter 2). The digital transformation goes well beyond the world of work, affecting many aspects of daily life. Students, parents, consumers and citizens need to have the skills to access, filter and process information, to perform the tasks that can be done through the Internet and to benefit from the new opportunities offered by the digital era (Chapter 4).

At the same time, digital transformation is characterised by an accelerated pace of change, and uncertainty in how and how fast technology will spread throughout countries. Putting too much emphasis in initial and advanced education on the development of specific skills that are important today (such as specific ICT ones) could lead to a high rate of skills mismatches among workers if these skills are no longer needed when this cohort enters the labour market. Workers and people lacking the readiness to learn face bigger risks of being displaced at work and feeling excluded from societies. In this context, lifelong learning is a crucial policy response to the uncertainty about future skills needs. As workers and citizens, people have to be able to adjust their skills sets continuously to new needs.

Although a diversified skillset can help individuals be resilient in digital economies and societies, labour markets demand students and workers who are specialised in some knowledge areas and have specific skills. Policies that support the provision of accurate, updated and usable information about labour market and skills needs are a key foundation for effective lifelong learning systems. It is also crucial to ensure that education and training systems are flexible enough to integrate this new information and react to changing skills needs.

Information on skills can decrease uncertainty, but only if it reaches individuals and informs their actions. Adults who report being interested in learning and who engage most in learning tend to have high levels of education and skills, to be younger, employed, in higher positions in their firms, and in larger firms (OECD, 2005[7]; Cedefop, 2015[8]; OECD, 2018[9]). That means special efforts need to be made to convey information on skills effectively to those who are likely to need it most, such as low-skilled individuals most at risk of job transformation or displacement.

Promoting high-quality lifelong learning for all

To prepare students to succeed in a complex and digitalised world, OECD countries are deepening and broadening what students learn in formal education. This important strategy acknowledges that strong cognitive skills acquired early in life are a foundation for developing well-rounded skills and fostering interest in continuing to learn throughout life.

Many countries are focusing on teaching new competencies from an early age. The number of countries that include in the pre-primary curriculum skills concerning health and well-being rose from 50% in 2011 to close to 90% in 2015, ethics and citizenship from less than 20% to 80%, ICT skills from less than 10% to 40% and foreign languages from less than 5% to 40% (OECD, 2017[10]).

In primary and secondary education as well, the broadening of the curriculum has focused on a range of skills, including digital competence, creativity, the ability to think critically and openly, and the ability to act ethically. Since 2012, the teaching of "computing" – which covers computer science, digital literacy and information technology (IT) – has been compulsory in English schools from ages 5 to 16,. Portugal introduced in 2017 a guidance document to be followed by all schools that sets out the knowledge, competencies and values to be acquired by all students upon completing upper secondary education. The guidance focuses on the ability to navigate a complex world competently through critical thinking, resilience and the ability to learn throughout life. Initiatives to expand the curriculum need to be carefully balanced, however, with the risk of overburdening children (OECD, 2018[11]).

In countries that have incorporated ICT skills in the curriculum, teachers need training in ICTs and often report this need. For instance, a review of the ICT curriculum in England highlighted the need to improve the attractiveness of the teaching profession for professionals with ICT skills, to provide more relevant continuous training for current teachers, and to create qualifications recognising immediate levels of ICT skills (The Royal Society, 2017[12]).

For over a decade, countries across the OECD have been tackling the need for teachers to develop ICT skills through a range of policies, from developing national plans promoting this goal, to introducing compulsory training, national accreditation standards or national certification for teachers. Denmark, for instance, has developed a voluntary Pedagogical ICT Licence that combines pedagogical knowledge of ICTs and basic ICT skills training, and has become a European standard in the provision of ICT skills to teachers. Implemented at first for in-service training, this approach was expanded to initial teacher education and general upper secondary education. While not mandatory, the licence is integrated into the curriculum of student teachers who graduate from teacher education colleges (Rizza, 2011[13]).

Policies that encourage the development of high-quality, equitable primary and secondary systems play a vital role in equipping all youth with key skills that form the foundation for learning in a digitalised world. Several policy approaches have been identified that foster quality education systems: well-designed curricula; early and targeted interventions to equip youth, especially those facing barriers, with key cognitive skills; a well-trained teaching workforce prepared to deal with an increasingly diverse student body and to teach new types of skills; and measuring quality by focusing on the outcomes of education rather than on how much spending has increased (OECD, 2018[14]). Similarly, policies that encourage universal participation in primary and secondary education include extending the duration of compulsory education to 18 years of age, in countries such as Belgium, Chile, Germany, the Netherlands or Portugal; enforcing school attendance; identifying students lagging behind as early as possible; and concluding agreements between national and local authorities to combat school dropout, as in the Netherlands, or reduce grade repetition, as in Portugal.

Vocational and educational training (VET) should be closely aligned with the needs of the labour market and flexible enough to adapt to the rapid changes taking place in the working environment. Since the labour market is demanding higher levels of skills, the traditional VET system aimed at manual and routine jobs has become outdated. Modernised VET systems should prepare students with a broad range of performance levels for an increasingly demanding labour market. VET systems need to ensure high-quality foundation skills and work-based training so that students develop a broad range of skills, from cognitive to technical ones.

It is also important that there are flexible pathways between VET and the academic/general track, so that students can move from one to the other. Countries such as Singapore and the Netherlands have VET systems that equip students with a broad and high level of skills, and have designed flexible systems with several paths that are offered at early ages; these models have shown to be compatible with achieving high quality and equity.

Ensuring equal access to higher education is vital to help people adapt to a digital world of work. The share of people aged 25-34 holding a tertiary degree has increased to 40% on average in OECD countries. In many countries, however, there remain large gaps in access between students with lower and higher socio-economic status. Policies to improve access include financial assistance; information and guidance; and academic and other support to help students enter and complete higher education (OECD, 2008[15]; Jongbloed and Vossensteyn, 2016[16]).

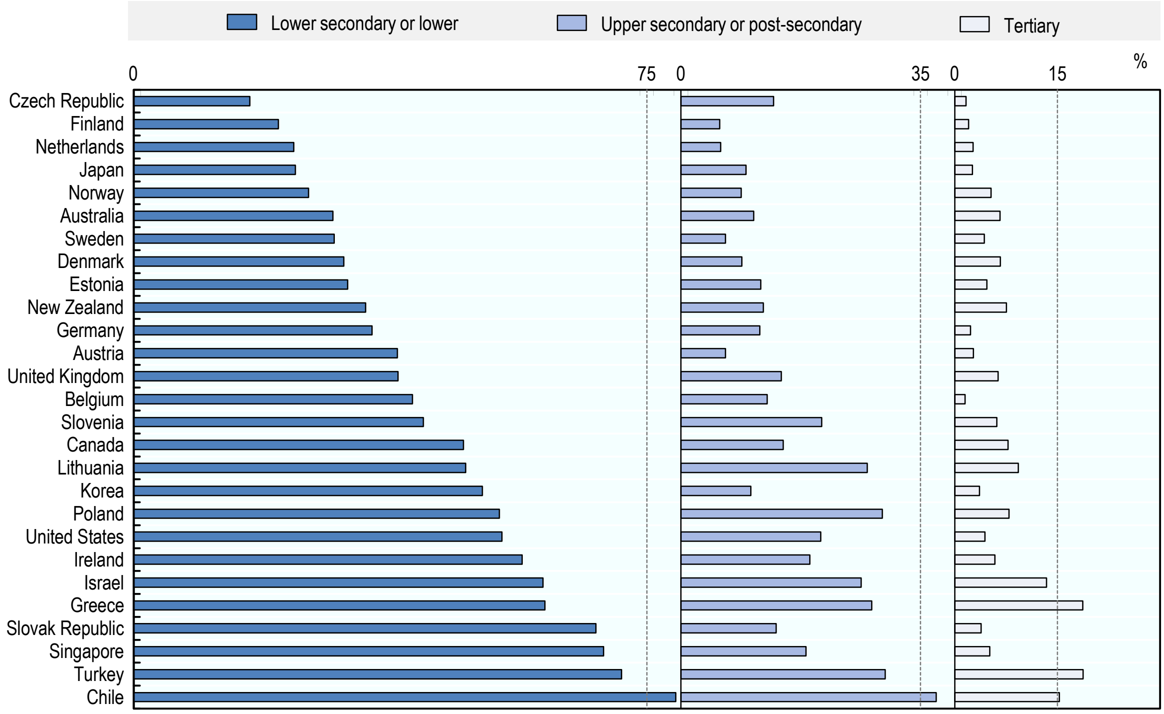
Helping students understand the labour market relevance and returns of higher education can also encourage participation and decrease uncertainty, particularly for groups who may be hesitant to invest in learning after secondary education. Australia and the United Kingdom, for instance, have government-sponsored websites that provide detailed information, including student satisfaction by programme, graduates employment outcomes and employers' views on the attributes of recent graduates (OECD, 2018[17]).

Information alone is not always sufficient to motivate students to enter higher education, however, especially those from low-income families. Several recent randomised field experiments in the United States and Canada show that assistance with applying for higher education and financial aid, provided at times where individuals have to be present (e.g. during class when targeting students, or during a meeting with a tax accountant when targeting parents) can boost rates of application to, and enrolment in, higher education (Oreopoulos and Ford, 2016[18]; Bettinger et al., 2012[19]).

Holding a tertiary degree does not always guarantee a high level of skills, however, as the quality of education systems and educational outcomes varies within and across countries. On average, around 7% of those aged 20-34 with a tertiary education degree lack basic skills, and more than 43% of those with at most lower secondary education (Figure 6.2). There are important variations between countries, especially regarding the share of young adults with lower secondary education who lack basic skills. Getting most pupils through secondary education, raising the quality of lower secondary education to that of the best performers (Denmark, Finland, Japan, the Czech Republic and the Netherlands) and improving the quality of some tertiary programmes would reduce the incidence of basic skills deficits.

Figure 6.2. Education levels linked with lacking basic skills

Share of 20-34 year-olds lacking basic skills, by education level, by country and education level (%)



Note: Individuals lacking basic skills score at most *Level 1* (inclusive) in literacy and numeracy and at most *Below Level 1* (inclusive) in problem solving (including failing ICT core and having no computer experience). The three education categories are constructed from the 1997 International Standard Classification of Education (ISCED): 1) Lower secondary or less (ISCED 1, 2, 3C short or less), 2) Upper secondary or post-secondary (ISCED 3A-B, C long, 4A-B-C), 3) Tertiary (ISCED 5B, 5A, 5A/6). Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.

Sources: OECD calculations based on OECD (2012[20]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and OECD (2015[21]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac /publicdataandanalysis

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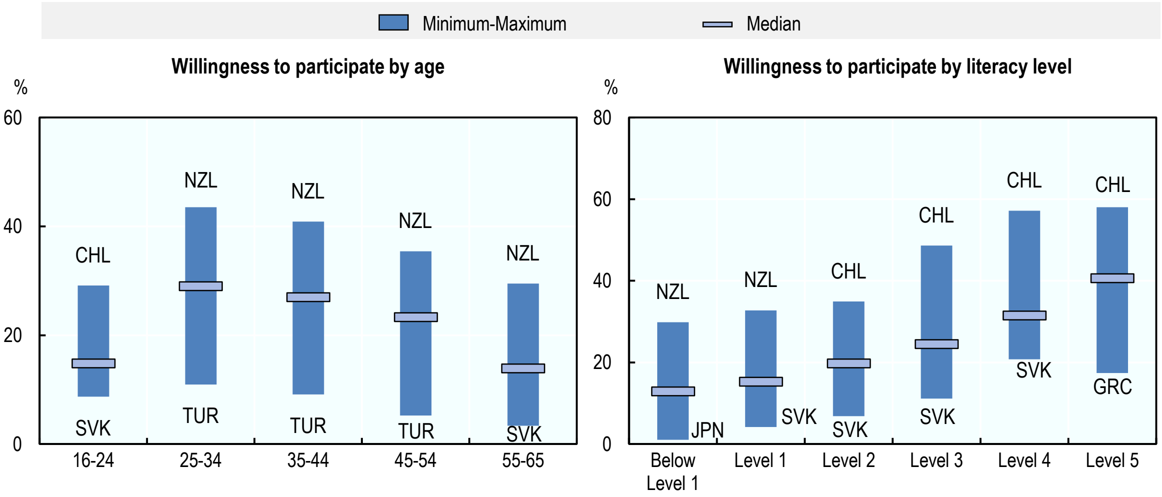
Overcoming the barriers to learning in adulthood is critical to deal with fast-changing skills demand. Adults have an increasing array of learning options, including formal education, short non-formal learning opportunities, informal learning on the job, and online learning opportunities such as MOOCs (Chapter 5). However, most adults report not being interested in learning. Of those who report interest, many identify the cost of learning as a reason not to engage in learning, along with a lack of time, of suitable and accessible options, or of employer support. The willingness to engage in learning varies significantly by age and skill level, and across countries (Figure 6.3). Evidence suggests that workers more exposed to the risk of automation are less likely to participate in training (Figure 6.4).

Figure 6.3. Willingness to participate in adult learning by age and skill level



Sources: OECD calculations based on OECD (2012[20]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and OECD (2015[21]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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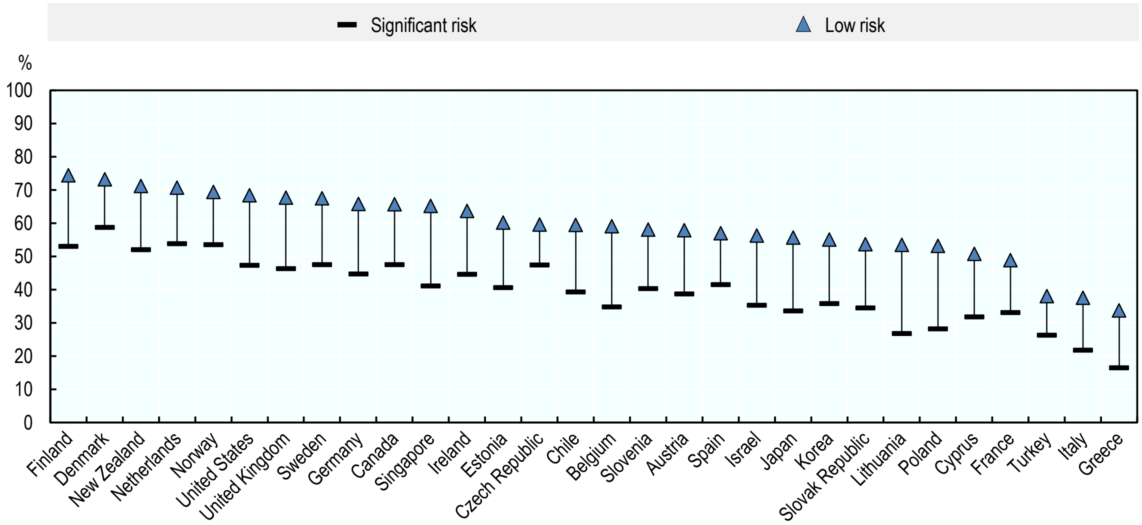
Many countries have thus developed a range of policies to promote lifelong learning, including: i) raising awareness of the returns of skills through targeted information and guidance, ii) creating flexible, shorter, modular types of learning opportunities, recognised as part of national qualifications framework, iii) improving the labour market relevance of adult learning opportunities, even when they target the acquisition of basic cognitive skills, iv) recognising prior learning, and v) a range of learning, financial and social supports to address specific barriers to learning faced by low-skilled and disadvantaged adults (Windisch, 2015[22]; European Commission, 2015[23]).

Policies that promote more efficient use of skills can help workers improve their skills while increasing firms' productivity and employees' wages. In Australia and Canada, these practices are often developed by firms as part of their human resources strategies. In Nordic countries, governments work with employers and employees' organisations to develop effective skills utilisation approaches and workplace innovations that can help boost both productivity and worker well-being (Stone, 2011[24]).

Enhancing participation in learning by adults who are either unemployed or outside of the labour force, or who are self-employed or employed in the "gig economy", requires an effective package combining employment protection legislation and active labour market policies, as well as social protection and taxation systems. This is discussed later in the chapter.

Figure 6.4. Participation in job-related adult learning by risk of automation

Share of workers participating in adult learning (in the last 12 months)



Note: Significant risk is defined jobs with a risk of automation over 50%, low risk as jobs having a risk of automation of at most 50%. Belgium refers to Flanders only, United Kingdom to England and Northern Ireland. Training refers to formal or non-formal job-related adult learning.

Note by Turkey:

The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue".

Note by all the European Union Member States of the OECD and the European Union:

The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

Sources: Nedelkoska and Quintini (2018[25]), "Automation, skills use and training", https://doi.org/10.1787/2e2f4eea-en (accessed on 05 February 2018), using PIAAC data in OECD (2012[20]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and OECD (2015[21]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink http://dx.doi.org/10.1787/888933974691

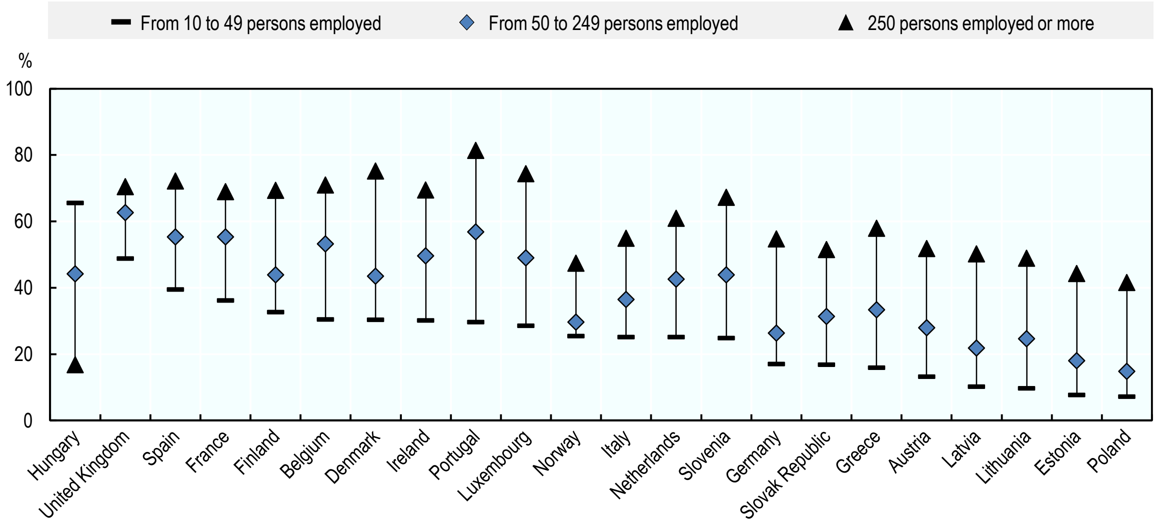
Anticipating changes in skills needs and guiding careers in a digital world

In an increasingly digitalised world of work, policies and tools to assess current skills needs and predict skills that may be in demand in the future are of crucial importance. A widespread approach in OECD countries consists of assessing and forecasting sector-specific and occupation-specific skills based on projections of employment needs, through skills assessment and anticipation (SAA) systems. Strong SAA systems need to *i)* define clear objectives for SAA exercises, *ii)* systematically use several quantitative and qualitative sources, and *iii)* involve various stakeholders in the production, dissemination and effective use of skills needs information (OECD, 2016[26]; OECD, 2017[27]; ILO, 2017[28]).

Mechanisms are necessary that ensure the information produced feeds into policy-making, is taken into account for education and training decisions, and reaches main actors. Evidence from some European countries shows that small firms are much less likely than big ones to assess their future skills needs (Figure 6.5). Providing information on future skills needs to firms at occupation or industry level – including to small firms – might help them make better training and recruitment decisions for the future.

Figure 6.5. Enterprises that assess their future skill needs by size group

Percentage of all enterprises, excluding those with less than 10 employees



Note: Share of enterprises declaring they "always" assess their future skills needs.
Source: Eurostat (2015[29]), *Continuing Vocational Training Survey (CVTS)*, https://ec.europa.eu/eurostat/web/education-and-training/data/database.

StatLink http://dx.doi.org/10.1787/888933974710

To facilitate co-ordination among stakeholders, the central government plays a lead role in countries such as France, South Africa, and the United Kingdom. In Portugal, a joint agency of the Ministry of Education and the Ministry of Labour, Solidarity and Social Security oversees the SAA system in collaboration with municipal authorities (OECD, 2018[30]). Other countries, such as Canada and the Czech Republic, use Sector Skills Councils to co-ordinate the production and use of skills needs information. In 2018, Canada launched the Future Skills initiative to develop and assess new approaches to identifying emerging skills that are in demand and options to improve the effectiveness of jobs and training programmes (Government of Canada, 2018[31]). An objective is to share innovative approaches to these issues in close co-operation with several stakeholders, including representatives from the manufacturing industry. The initiative includes a Future Skills Centre to bring together expertise on these domains and a Future Skills Council that will report to the Minister of Employment, Workforce Development and Labour.

Exercises that anticipate growing occupations and future skills needs can be complemented by studies on training policies to facilitate transitions between occupations (Chapter 3). To offset the impact of new technologies on occupations, cost-effective training policies should help workers move to occupations that have lower risks of automation and are not too different from occupations of origin in terms of skills requirements, knowledge area and the tasks performed on the job.

Policies supporting career guidance are key to transform information on skills needs into knowledge that can inform learners' decisions. Emerging evidence suggests career guidance can help improve the employment and earnings of participants, boost educational outcomes, and improve self-confidence and decision-making skills (Musset and Mytna Kurekova, 2018[32]).

Countries such as Germany, Ireland and Scotland have developed comprehensive career guidance services offering access at any point in life and a combination of digital tools for self-guided exploration and face-to-face services for higher levels of need. In Scotland, career guidance is recognised as a specialist profession, with a requirement for both initial and continuous professional training (Musset and Mytna Kurekova, 2018[32]).

To address the uncertainty of future skills needs, policies also need to make education and training systems more relevant to the labour market and more reactive to changes.

Work-based learning is critical to strengthening the links between the education system and the labour market. By providing workplace training, employers demonstrate their support for such programmes. Workplaces provide an environment conducive to developing skills needed in the labour market (OECD, 2015[33]).

In countries with strong apprenticeship systems, the need for specific policies to encourage provision of work-based learning depends on the costs and benefits of training for employers. In Germany, firms show a strong willingness to make net investments in apprenticeships, as 60% of apprentices remain in the firm after training. In Switzerland, by contrast, employers are less willing to make upfront investments, due to higher mobility of apprentices after training has ended. Firm size matters: investments in training are particularly challenging for small and medium enterprises, while retention rates are lower (Mühlemann, 2016[34]). This suggests that policy interventions may be warranted when labour market conditions limit employers' incentives to provide training, and in countries and sectors with large shares of small enterprises.

Several regions and countries also seek to encourage work-based learning in higher education. In Ontario (Canada), greater use of work-based training has been promoted through tax credits, better information about the support available to employers and the skills of students, and flexible work-time and supervision requirements. It is also important for higher education institutions to co-ordinate their approaches to employers, to avoid excessive or duplicative demands (Sattler and Peters, 2012[35]). In Portugal, making internships mandatory in some programmes was found to strengthen partnerships between higher education institutions and employers and to boost employability more than other forms of work-based learning. Further, several shorter internships can have a superior effect on employability than longer, single internships, by allowing students to explore different work functions and workplaces (Silva et al., 2016[36]).

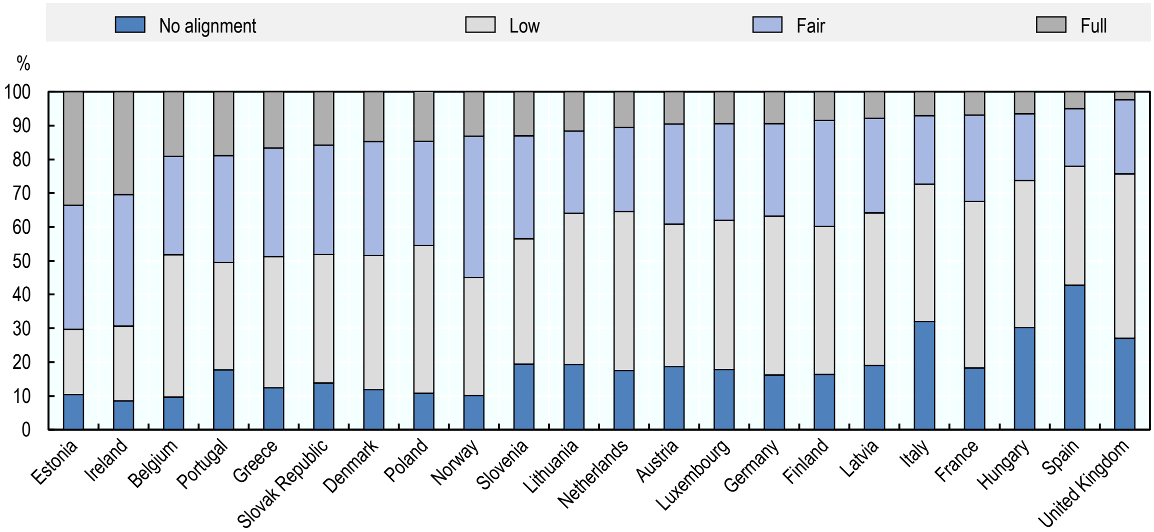
Fostering entrepreneurial skills through education and training is another way to prepare workers for non-linear career paths and help them seize the opportunities of the digital economy. As the gig economy continues to expand, entrepreneurial skills become increasingly required for workers who wish to provide their services through online platforms. In OECD countries, entrepreneurship education in universities largely focuses on business creation. However, embedding entrepreneurship education within research and teaching is seen as increasingly valuable to develop entrepreneurial competences such as creativity and risk-taking (Benneworth and Osborne, 2015[37]). In addition, policies that encourage a shift at all education levels towards a learner-centred approach to teaching can help provide key entrepreneurial skills (Penaluna and Penaluna, 2015[38]).

Training provided on the job also need to respond to the needs of firms and labour markets. Workers' training activities need to be aligned with the identified skill needs of the company (OECD, 2019[39]). When comparing the top three skills that firms report as important for the development of the firm with the three most important skills targeted in training activities, there is only a complete overlap for 13% of firms across European

OECD countries (Figure 6.6). This misalignment arises partly because some firms only provide compulsory training opportunities, such as health and safety training. This type of training should not substitute for training that help develop the skills workers need to face changes on the labour market.

Figure 6.6. Overlap between firms' development and training priorities

Percentage of firms at different degrees of alignment between the skills they consider as the most important for further firms' development and skills targeted through training, 2015



Note: Excludes firms with fewer than 10 employees. Countries are ranked by their average degree of alignment. The degree of alignment is calculated as the overlap between the top three development priorities of the firms and their top three training priorities (in terms of training hours). Each firm can score either zero (i.e. no overlap), low (i.e. one development priority is also a training priority), fair (i.e. two development priorities are also training priorities) or full alignment (i.e. complete overlap between development and training priorities).
Source: OECD (2019[39]), *Getting Skills Right: Future-Ready Adult Learning Systems*, https://dx.doi.org/10.1787/9789264311756-en.

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Co-ordinating policies to offset the unequal geographic impact of digitalisation

The digital transformation can exacerbate inequalities between cities and regions. Access to the Internet varies between regions within countries. High-tech firms are concentrated in a small number of geographic areas where most job creation related to new technologies takes place while other areas have to face major job destruction. At the same time, digital technologies facilitate remote working and work practices that take advantage of ICT tools, thus making learning and job opportunities more ubiquitous.

Offsetting the unequal geographic impact of digitalisation is not easy. Many policies, including education and skills policies, tend to reinforce each other in exacerbating regional disparities unless they are well designed. The accumulation of disadvantages in some regions creates dissatisfaction and a sense of injustice among the population. This section discusses policies that can ensure the benefits of digitalisation are more equally shared within countries.

The benefits of digitalisation are shared unequally within countries

Digitalisation has affected regions and cities within countries unequally. Skills-related policies can influence this divide. The rate of convergence in economic prosperity between regions and cities within OECD countries has undergone a sharp slowdown since the 1980s. The advent of the personal computer and the many technologies it enabled has contributed to this slowdown. Other factors include the offshoring consequences of globalisation, declining labour mobility in some countries, and agglomeration economies (Box 6.1) (Rosés and Wolf, 2018[40]).

Box 6.1. Agglomeration economies: Why economic activity is so highly concentrated geographically

About three in four Americans live in cities, yet these cities span only 2% of the land area. Moreover, despite not needing any specific raw materials, software producers in the United States are highly concentrated in the area dubbed Silicon Valley, between San Francisco and San Jose (Rosenthal and Strange, 2004[41]).

The explanation lies in what are called agglomeration economies, or economies of scale generated by the concentration of factors of production in geographic space (Duranton and Puga, 2004[42]; Rosenthal and Strange, 2004[41]). Building on Alfred Marshall's (1890[43]) taxonomy, economists have distinguished three main mechanisms underlying agglomeration economies: sharing, matching, and learning (Duranton and Puga, 2004[42]).

Sharing: In densely populated areas, firms and workers can gain from having access to a wider range of input supplies due to the proximity to a large final goods industry as well as through the sharing of high fixed-costs indivisible goods and facilities such as sports stadiums, parks and airports.

Matching: The spatial concentration of firms and workers can improve the quality of the match between workers' skill supply and firms' skill demand as well as increase the probability of a match taking place since there are more workers and firms to choose from.

Learning: Workers in densely populated cities can benefit from the informal exchange of ideas, management practices and new technology uses with other workers which increases their productivity and promotes faster innovation. This mechanism implies there are economies of scale whose benefits accrue over time or dynamic agglomeration economies.

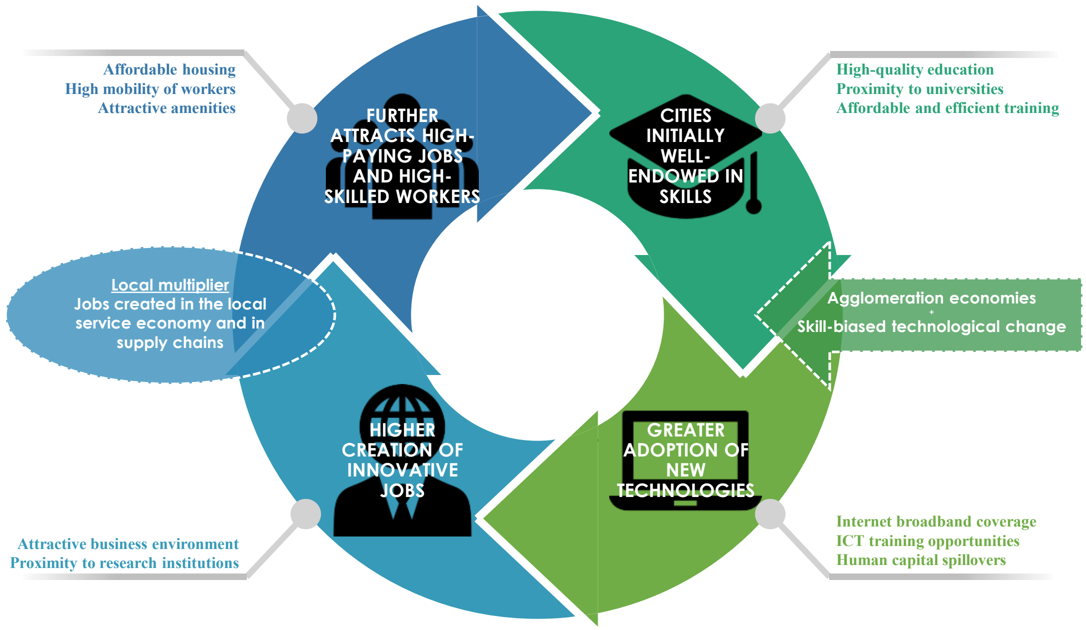
Sources: Rosenthal, S.S. and C. Strange (2004[41]), "Evidence on the nature and sources of agglomeration economies", http://dx.doi.org/10.1016/S0169-7218(04)07049-2; Duranton, G. and D. Puga (2004[42]), "Micro-foundations of urban agglomeration economies", http://dx.doi.org/10.1016/S0169-7218(04)07048-0; Marshall, A. (1890[43]), *Principles of Economics*, Macmillan, London.

In the United States, computer adoption and new computer-related jobs were more likely to be observed in the 1990s and 2000s in areas that already in the 1980s had a high stock of high-skilled workers (proxied by the share of college-educated workers) (Lin, 2011[44]; Berger and Frey, 2016[45]; Beaudry, Doms and Lewis, 2010[46]). The complementarity between technology and skills has enabled these areas to experience faster growth in income and skill endowment than less-skilled cities (Giannone, 2017[47]; Rosés and Wolf, 2018[40]).

At the same time as new technology-related jobs were being created in cities with highly skilled populations, old manufacturing hubs or areas poorly endowed in tertiary-educated individuals were falling behind. Although it may have seemed that the ubiquity of digital technologies would lessen geographic disparities, rendering physical proximity irrelevant, the opposite seems to have held so far. The benefits of digitalisation, reinforced by agglomeration economies, have been highly concentrated spatially, although there are signs that some firms are starting to take advantage of digital technologies to locate outside high-tech regions and escape high living costs (The Economist, 2018[48]).

High-skilled individuals attract technology-intensive firms and industries, and high-paying jobs, and high-paying jobs further attract high-skilled workers. Low-skilled jobs in the local service economy also grow to cater for the needs of these firms and workers. This virtuous cycle underpins much regional and urban success (Figure 6.7).

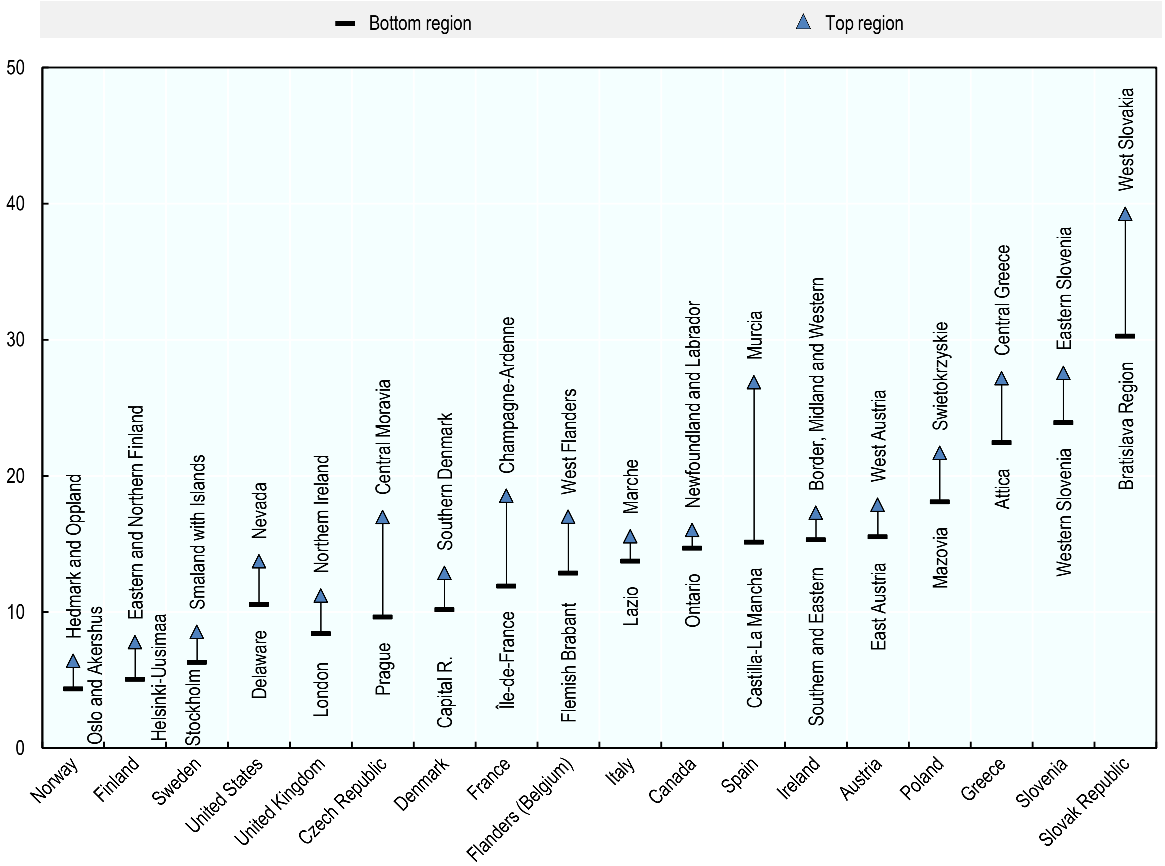
Figure 6.7 Mutually reinforcing beneficial local effects of skills and technology



In the future, automation may deepen regional inequalities as the number of jobs at high risk of automation varies significantly between regions within countries (Figure 6.8) (OECD, 2018[49]). Regions with the lowest share of tertiary-educated workers also have the highest share of jobs at high risk (OECD, 2018[49]). Given that less educated workers tend to be less geographically mobile, this phenomenon threatens to further aggravate inequalities between regions. Some regions will be characterised by high unemployment and low productivity while others will thrive, with high employment and productivity.

Figure 6.8. Share of jobs at high risk of automation within countries

Percentage of jobs at high risk of automation, highest and lowest performing TL2 regions, by country, 2016



Note: High risk of automation refers to the share of workers whose jobs face a risk of automation of 70% or above. Data from Germany corresponds to the year 2013. Except for Flanders (Belgium), for which subregions are considered (corresponding to NUTS2 level of the European Classification).

Source: OECD (2018[49]), *Job Creation and Local Economic Development 2018: Preparing for the Future of Work*, https://dx.doi.org/10.1787/9789264305342-en.

StatLink http://dx.doi.org/10.1787/888933974748

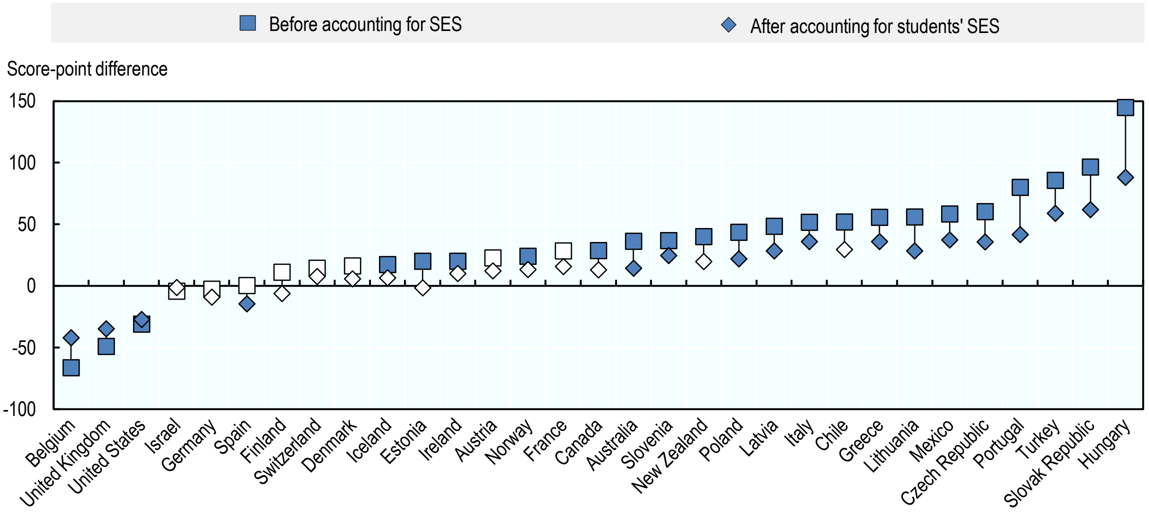
Equalising children's education opportunities

Human capital is a key driver of economic growth, both at the national (Barro, 1991[50]) and subnational levels (Gennaioli et al., 2013[51]). The emergence of the knowledge economy has heightened its importance. Inequities in the skills endowment of regions explain part of the differences in regions' economic performance. Thus an education system that is affordable, accessible and high-performing, at every age level, can help local economies that have been left behind to catch up by improving their skill endowments.

A better prepared workforce increases a region's economic performance and can help attract firms that offer job opportunities matching the local talent pool. It can also spur entrepreneurial activity. Skills also facilitate the adoption of new technologies and new management practices that boost workers' productivity (Andrews, Nicoletti and Timiliotis, 2018[52]). There are also significant non-monetary benefits from having a better skilled workforce, including lower crime rates, lower health costs and greater social cohesion, which may together contribute to making an area more prosperous (OECD, 2010[53]).

In many OECD countries, students in cities (of over 100 000 people) score higher in science than their rural counterparts (in areas of less than 3 000 people), though the difference is not always statistically significant (Figure 6.9) A gap of 30 points, which corresponds to the average scores gap between urban and rural students in OECD countries, is the equivalent of roughly one academic year (OECD, 2018[54]). Results in reading and mathematics match these findings.

Figure 6.9 Rural-urban differences in students' performance (PISA 2015)



Note: These figures display, for each country, the average difference in PISA scores between 15-year-old students in rural and urban schools without any controls and accounting for the socio-economic status of the student. Statistically significant differences at the 5% are marked in a darker tone. Schools in rural area or village are defined as being located in "a village, hamlet or rural area with fewer than 3 000 people," while schools in cities are defined as being located in a city of over 100 000 people. A student's socio-economic status is estimated by the PISA index of economic, social and cultural status (ESCS), which is derived from several variables related to students' family background such as parents' education, parents' occupations, a number of home possessions that can be taken as proxies for material wealth, and the number of books and other educational resources available in the home (OECD, 2016, p. 205[55]).
Source: OECD (2015[56]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

StatLink http://dx.doi.org/10.1787/888933974767

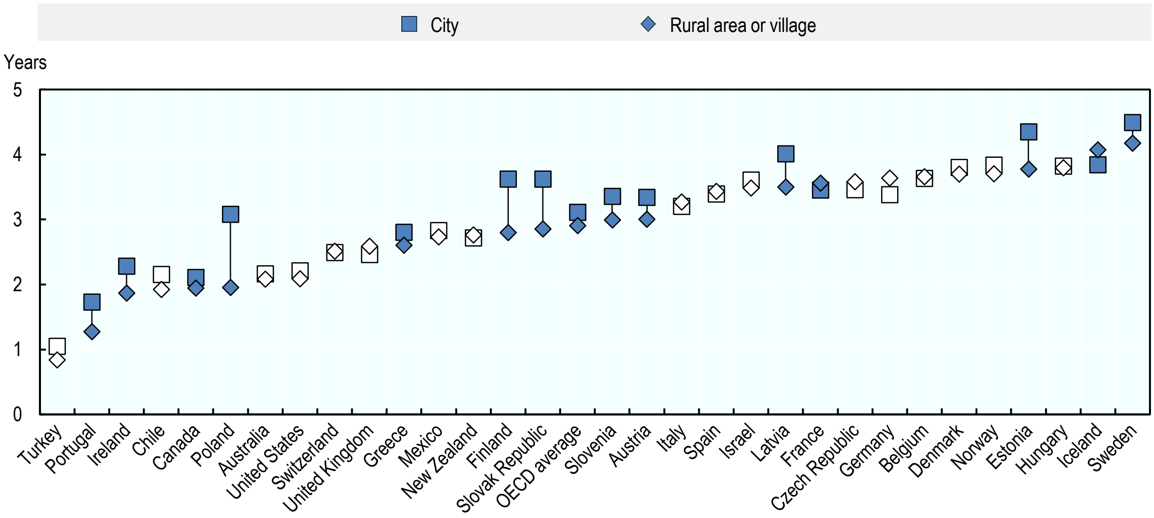
Students' socio-economic background does not explain all the difference in scores, suggesting that school characteristics and the local environment may also play a role. Schools in rural areas tend to have less responsibility for resource allocation; have a harder time recruiting, training and retaining teachers; are smaller in size and are less likely to have a high proportion of qualified teachers (OECD, 2018[54]). What happens outside schools in children's neighbourhoods also matters crucially for children's acquisition of cognitive and non-cognitive skills (Goux and Maurin, 2007[57]; Bell et al., 2017[58]). Narrowing these gaps would constitute a first step in equalising economic opportunities between regions within countries.

Policies

As children's early years are essential for the development of their cognitive and socio-emotional skills (Heckman, 2006[59]), pre-primary school can help even up opportunities between children from privileged and from disadvantaged backgrounds, as well as between those living in sparsely populated rural areas and those in thriving dense cities. Countries need to ensure that young children of all regions can attend high-quality pre-primary education.

The urban-rural gap in the number of years attending pre-primary school is significant in several OECD countries (Figure 6.10). On average across OECD countries, students attending a school in a rural area or village report having attended two months less of pre-primary school than their urban counterparts.

Figure 6.10. Average number of years attending pre-primary school, by school location



Note: This figure displays, for each country, the average number of years attending pre-primary school as self-reported by the 15-year-old students themselves between those currently in a rural or urban school. Statistically significant differences at the 5% are marked in a darker tone. Schools in rural area or village are defined as being located in "a village, hamlet or rural area with fewer than 3 000 people," while schools in cities are defined as being located in a city of over 100 000 people.
Source: OECD (2015[56]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/, Table II.6.51.

StatLink http://dx.doi.org/10.1787/888933974786

These recommendations do not apply just to rural areas that face specific challenges linked to their low population levels. Cities and regions as a whole should ensure that the education they provide equips their residents with at least basic cognitive and interpersonal capacities to improve their productivity and generate positive local spillovers. Many geographic divides are between growing and lagging-behind cities or between city centres and suburbs.

Incentives to motivate the best teachers to move to the least privileged schools can help bridge gaps between advantaged and disadvantaged schools. In many countries, however, including some that compensate for disadvantage in schools by allocating more teachers to those schools, teachers in the most disadvantaged schools are less qualified and/or experienced than those in the most advantaged schools (OECD, 2018[60]). Combining the flexibility of recruitment and management that comes from greater school autonomy with compensatory funding mechanisms appears to enable the most challenging schools to attract the best teachers.

Harnessing the potential of universities

Universities can boost regional development (Drucker and Goldstein, 2007[61]; OECD, 2007[62]; Bonaccorsi, 2017[63]), though the magnitude of the effect crucially depends on the local context (Bonaccorsi, 2017[63]). Universities can increase the supply of skills, by educating individuals and attracting others from outside, and the demand for skilled workers, through research and development activities (Moretti, 2013[64]; Abel and Deitz, 2012[65]). The local return to higher education is significant, not only for the individual but also for the community. Skilled university graduates can attract firms with high-paying jobs, further attracting new high-skilled workers and thereby initiating a virtuous cycle described in Figure 6.7

Proximity to top academic experts is crucial for the innovative sector, even more so than proximity to venture capital firms or access to government funding (Zucker, Darby and Armstrong, 2002[66]; Zucker and Darby, 2014[67]). Private-sector start-ups in highly technical fields such as artificial intelligence, robotics or biotechnology need to stay up to date with the latest academic research and physical proximity facilitates this process. Academic stars are often personally involved in or leading such start-up ventures (Gideon, 2016[68]).

Universities can also improve individuals' geographic mobility. One study from the United States found that attending college had a causal impact on individuals' interstate migration (Malamud and Wozniak, 2012[69]). The mechanisms through which university attendance improves geographic mobility are unclear and may be related to the acquisition of general cognitive skills or the possibility to benefit from a more geographically dispersed labour market for university-acquired skills and degrees.

Using data from the 2014 European Tertiary Education Register (Box 6.2), it is possible to map the location of universities in some European countries. Higher education institutions are very unequally distributed within European countries (Figure 6.11). Because the size of the regions in the Nomenclature of Territorial Units for Statistics (NUTS 3) differs markedly between countries, comparisons are to be taken with some precautions. In the vast majority of these European countries, over a quarter of regions do not have any universities. Universities tend to be located in densely populated areas, particularly in capital cities such as Istanbul, Paris and Warsaw. Research-oriented universities – those delivering PhD-level degrees (ISCED 8) – which may offer the most potential for local growth, are even more highly concentrated.

Box 6.2. Geographic distribution of higher education institutions

The European Tertiary Education Register (ETER) is a European Commission initiative that collects information on higher education institutions (HEIs) in 35 European countries and Turkey. It provides data at the institution level on numerous dimensions such as basic administrative characteristics, geographic location and educational activities. The coverage is close to that of Eurostat for ISCED levels 6 (bachelor's degree), 7 (master's degree), and 8 (PhD) but limited at level 5 (short-cycle tertiary education) (Lepori et al., 2016[70]). Data from 2014 is used. The regional typology used in this analysis is the 2013 Nomenclature of Territorial Units for Statistics (NUTS) 3, which corresponds to small regions (*département* in France, *Kreis* in Germany).

There are two caveats for the analysis presented here. First, institutions in Luxembourg, Montenegro, Romania and Slovenia do not provide information on the highest degree they deliver, a variable used to identify PhD-granting (research) universities. Second, the way multi-site institutions are accounted for may lead to slightly underestimate university dispersion.

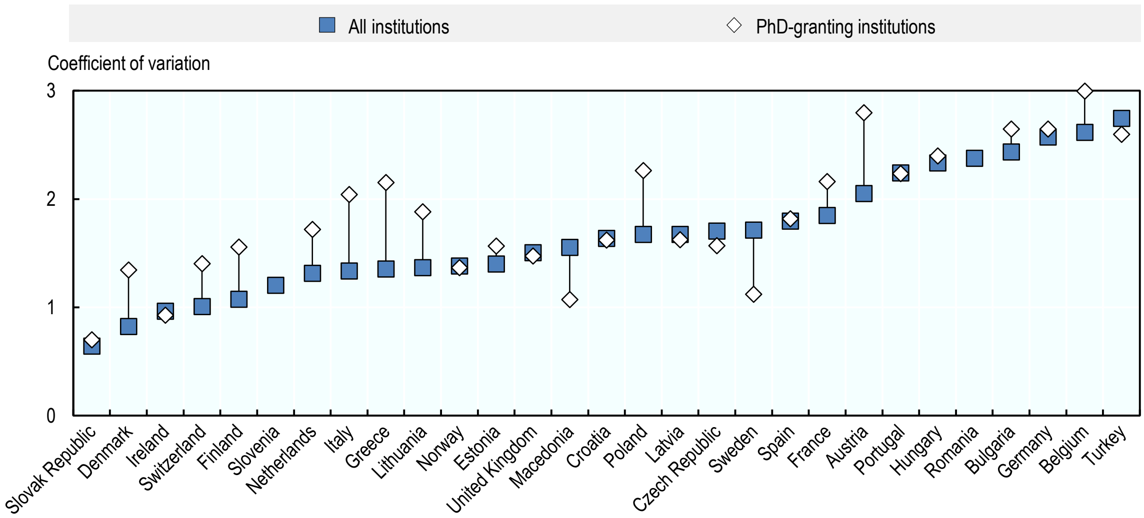
Source: Lepori, B. et al. (2016[70]), *The ETER Perimeter and Coverage: An In-depth Analysis*, https://www.eter-project.com/assets/pdf/ETER_perimeter_and_coverage.pdf (accessed on 29 August 2018).

The geographic dispersion of higher education institutions matters because distance to university is an important factor in shaping students' educational aspirations, as well as in the decision to attend university – and in particular an elite institution – though its role varies by country (Gibbons and Vignoles, 2012[71]; Parker et al., 2016[72]; Spiess and Wrohlich, 2010[73]; Frenette, 2006[74]). With the exception of Belgium, 15-year-old students in rural areas are significantly less likely to expect to complete a university degree than their urban counterparts (Figure 6.12). On average across OECD countries, children attending a school in a city of over 100 000 people are 19 percentage points more likely to expect to attend university than those attending a school in an area with less than 3 000 inhabitants.

This gap remains in a number of countries even after accounting for students' socio-economic status and maths proficiency, implying that environmental factors play a large role in shaping student expectations.

Figure 6.11. Dispersion of the number of higher education institutions (HEIs) and PhD-granting HEIs by country in 2014

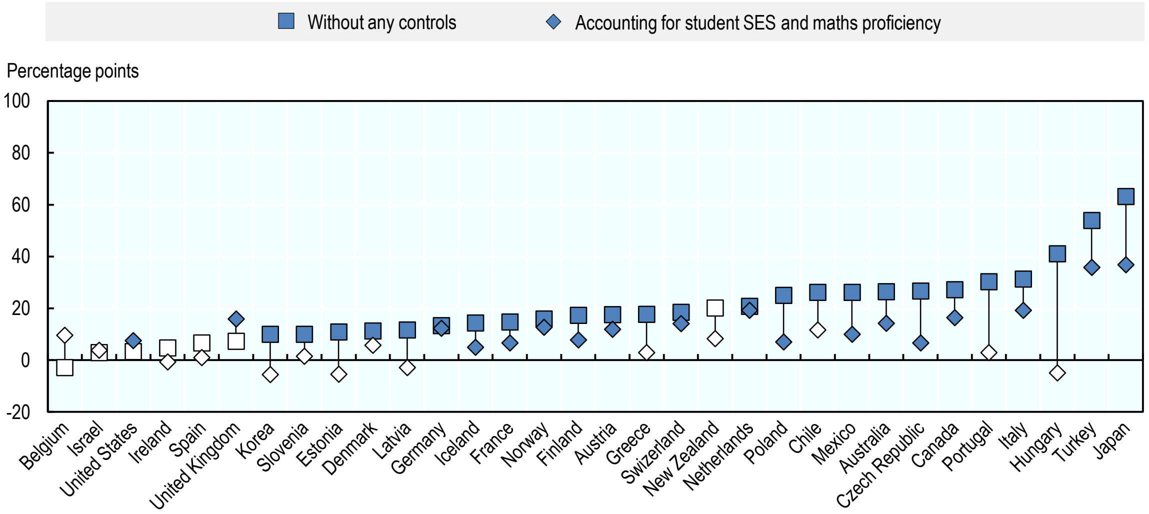
Coefficient of variation of the number of institutions per NUTS 3 region within a country



Note: This figure displays, for each country, a measure of dispersion, the coefficient of variation (standard deviation divided by the mean), of the number of higher education institutions and PhD-granting institutions per NUTS 3 region within a country in 2014. The NUTS classification corresponds to that from 2013.
Source: ETER (2014[75]), European Tertiary Education Register, https://www.eter-project.com/#/home.

StatLink http://dx.doi.org/10.1787/888933974805

Figure 6.12 Difference between urban and rural schools in share of students expecting to complete a university degree



Note: This figure displays, for each country, the difference between urban and rural schools in the share of 15-year-old students expecting to complete a university degree, without any controls and accounting for student socio-economic status and maths proficiency. Statistically significant differences at the 5% are marked in a darker tone. Schools in rural area or village are defined as being located in "a village, hamlet or rural area with fewer than 3 000 people," while schools in cities are defined as being located in a city of over 100 000 people. A student's socio-economic status is defined as explained in Figure 6.9's note.
Source: OECD (2015[56]), *PISA database 2015*, http://www.oecd.org/pisa/data/2015database/.

StatLink http://dx.doi.org/10.1787/888933974824

Policies

There are two main policy options to close this aspiration and attendance gap. First, to reduce the financial burden of attending an institution far from home, universities and public institutions could provide distance-based aid that would increase as a function of the prospective student's distance from the university (perhaps using precise expected travel time by train, bus or car rather than a simple radial distance). Information about this aid should be clearly advertised, with teachers communicating the specific details to students. Open education and open universities that provide options to enrol in tertiary programmes from remote areas can also bridge the aspiration and attendance gap between geographic areas (Chapter 4).

Second, role model, mentoring and outreach programmes by university students may help raise the aspirations of students who lack exposure to universities because of their schools' remoteness. Schools in areas far from any higher education institution could, for example, organise regular discussions between their students and former students who attended university. Other forms of mentoring programmes could conversely finance school trips to universities, where secondary students would be able to visit the campus, talk with current students and perhaps meet professors or attend classes.

Enabling geographic mobility

Increasing workers' ability to move from one geographical area to another can play a key role in lessening the differences in regional performance brought about by digitalisation. Enabling individuals to move from low-income to high-income areas increases labour supply in the high-income area and puts downward pressure on wages. In the medium run, this decreases income gaps between the two areas. The decline in such migration from low- to high-income areas in the United States may have contributed to the slowdown in regional convergence (Ganong and Shoag, 2017[76]).

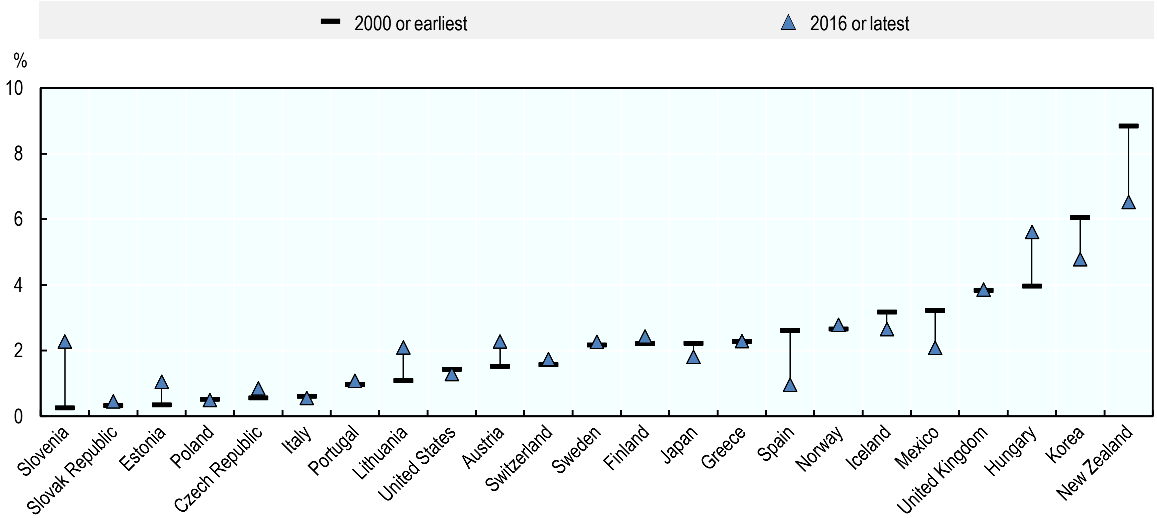
In some OECD countries, workers' geographical mobility has declined in recent decades (Figure 6.13). This phenomenon is particularly pronounced in Korea, Mexico, New Zealand and Spain. Even the United States, which is often thought of as a very mobile country, has experienced a slight decline in migration. There are many reasons why individuals do not move within and between countries. They have social ties where they currently live, there is uncertainty as to whether they will find a job if they move, and housing costs have reached very high levels in many booming areas. In addition, the industrial composition of areas has become more homogenous, reducing the need to move, and the Internet has enabled individuals to acquire information about potential new locations without having to live in a different place for some time (Kaplan and Schulhofer-Wohl, 2017[77]).

Improving coverage of digital infrastructures

The extent of access to broadband Internet varies significantly between regions within countries (Figure 6.14). On average across OECD countries, around four out of every five households had broadband Internet access at home in 2016. In Denmark, Iceland and Korea, the difference between the best and worst performing TL2 (large) region is less than 5 percentage points while it is above or close to 50 percentage points in Mexico, Russia and Turkey. Statistics computed at this large regional level may also hide significant disparities within regions.

Figure 6.13 Geographical labour mobility in 2000 and 2015

Percentage of individuals moving, within the same country, to another TL3 (small) region



Note: This figure displays the percentage of individuals, within a given country, that relocated to another TL3 (small) region in 2000 (or early 2000s) and in 2016 (or latest available). For each country, the years used are as follows: Slovenia: 2000-16; Slovak Republic: 2000-16; Estonia: 2000-15; Poland: 2000-16; Czech Republic: 2000-16; Italy: 2002-13; Portugal: 2001-11; Lithuania: 2001-15; United States: 2000-11; Austria: 2002-16; Switzerland: 2000-16; Sweden: 2000-16; Finland: 2000-16; Japan: 2000-16; Greece: 2001-11; Spain: 2000-16; Norway: 2000-16; Iceland: 2000-16; Mexico: 2000-15; United Kingdom: 2000-15; Hungary: 2000-16; Korea: 2000-16; New Zealand: 2001-13.
Source: OECD (2016[78]), *OECD Regional Database*, https://stats.oecd.org/Index.aspx?DataSetCode=REGION_DEMOGR#.

StatLink http://dx.doi.org/10.1787/888933974843

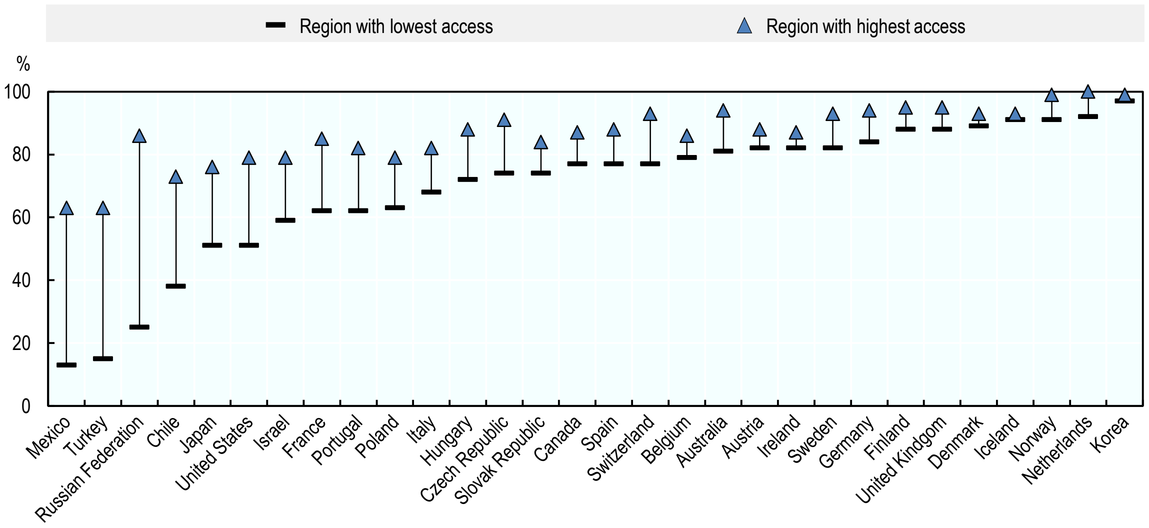
A priori, the reasons for such stark differences within countries in access to broadband Internet are not obvious. Such differences could be due to a lack of demand, (people not needing or wishing to have Internet access) inadequate supply (insufficient coverage of rural areas, as is often the case), or unaffordable Internet service prices. The fact that rural areas are still underserved by broadband Internet suggests that many countries can still improve the supply of Internet access throughout their territories.

Access to broadband Internet is essential for people and firms in many respects. It enables people to communicate with their friends and families, to shop online, to look for jobs or training opportunities, to access government services, to book medical appointments, to monitor bank accounts, and to keep up to date with current affairs and any other interests they may have (Chapter 4). It helps people of all ages acquire the digital skills that are crucial to navigate through the digital age. As for firms, it seems unthinkable today for a firm to establish itself in an area without or even moderately slow Internet access.

Moreover, firms' access to high-speed broadband Internet is a key enabler for the adoption of more advanced digital technologies such as cloud computing and sophisticated front and back office software that may increase productivity (Andrews, Nicoletti and Timiliotis, 2018[52]). It is thus crucial for regional convergence that national and regional broadband access policies prioritise full territorial coverage.

Figure 6.14. Regional differences in access to broadband Internet

Percent of households with Internet broadband access, by country, 2016



Note: The figure displays, for each country, the percentage of households with internet broadband access in the worst and best performing TL2 (large) region in 2016. Data is from 2016 for Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary Ireland, Italy, the Netherlands, Norway, Portugal, Slovak Republic, Spain and Sweden; 2015 for Australia, Japan, Mexico and Russian Federation; 2014 for Korea, Israel, Poland and Switzerland; 2013 for Chile, Turkey and the United Kingdom; 2012 for Canada and Iceland; and 2011 for the United States.

Source: OECD (2016[79]), *OECD Regional Database, Regional Social and Environmental Indicators*, https://stats.oecd.org/Index.aspx?DataSetCode=REGION_SOCIAL.

StatLink http://dx.doi.org/10.1787/888933974862

A co-ordinated policy response across policy areas and actors

Making the most of digitalisation requires a co-ordinated policy response across policy areas and actors. While education and skills policies are central in the response to the challenges brought by the digital transformation, other major policy areas also have an important role to play. Social protection, for instance, influences people's capacity to improve their skills, change career when needed and feel protected against labour market risks. Close alignment and interactions between various policy areas are important.

Identifying the range of relevant policies

The development of new technologies can stimulate countries' innovation, growth and productivity while offering people new economic and social opportunities. These opportunities are diverse. They include access to cheaper products and services for people and firms, new activities facilitated by online platforms, new and flexible work arrangements and business models, renting out real estate directly among individuals, and creating communities and interest groups that can translate into political impact.

A range of policies affect countries' and regions' capacities to make the most of digitalisation. Ensuring that policies and institutions facilitate and encourage lifelong learning for all is the cornerstone of the whole policy package. As discussed earlier in this chapter, strong lifelong learning systems in themselves require a combination of targeted policies to support broad participation in a high-quality and equitable range of education and training options.

Policies outside the skills domain also affect the extent and speed of the digital transformation, the demand for jobs and skills, and thereby the implications of the digital transformation for the labour market, productivity, and inequality. That means policies in various domains need to be co-ordinated to make the most of the digital transformation.

For instance, the explosion of economic and social activity online requires protection for the safety, privacy and security of online users, while ensuring that the benefits of online economic activity is broadly and fairly shared. Policies that help people to develop the skills and knowledge they need to protect themselves against new risks need to be co-ordinated with policies that affect the spread of online economic and social activity.

Intangibles such as software and data are highly mobile and firms can now disconnect their central location from where their users/customers and suppliers are located. These changes generate opportunities for firms in the digital technology sector to quickly reach "scale without mass", and monopoly or oligopoly situations. As a result, governments can find it difficult to use social, labour and tax policies to spread the benefits of digitalisation (OECD, 2015[80]).

Digitalisation also challenges governments' ability to maintain trust in democratic institutions and public services. The digital transformation is rapid and brings a multiplicity of players with diverse views into the economic, social and cultural realm. Institutional and policy responses, by contrast, are slower, and sometimes involve limited and uneven human attention (OECD, 2017[81]; Williams, 2018[82]). This gap underlines the importance of designing and co-ordinating policies well so that they can manage the various impacts of digitalisation and respond to rapid change by being well connected to the needs of citizens in a digital world.

Policies

In response to the digital transformation, the large majority of OECD countries have developed comprehensive national digital strategies, agendas or programmes with a series of objectives across several policy areas. In an OECD survey on the topic, countries' three top objectives were identified as: strengthening e-government services, further developing telecommunications infrastructure, and promoting ICT-related skills and competences (OECD, 2017[81]).

Countries need multi-dimensional policies that take advantage of the opportunities of digitalisation, mitigate its risks, or do both simultaneously (Table 6.1). Lifelong learning policies play a central role in that they are often a building block for other policies. For instance, accelerating digital adoption in firms to improve growth and productivity requires good skills among firm managers and employees. Lifelong learning can also help cushion the disruptive effects of digitalisation. It can provide access to high-quality learning opportunities for adults who are unemployed or at risk of displacement, facilitate access to employment, and limit reliance on social protection.

Innovation lies at the heart of the digital economy. Policies aimed at boosting innovation can play an important role in funding long-term research that firms are reluctant to invest in due to the scale of investment needed, the risk involved, or the risk that the resulting assets may be broadly available (non-excludable) (OECD, 2017[83]). Innovation policies can also focus on closing the divides in technology use and creation between OECD and emerging countries, between regions within countries, between younger and older people, and between women and men. Some of these policies include expanding digital infrastructure to ensure accessibility for all. Access alone is not sufficient, however. These policies need to be complemented by education and skills measures, aimed for instance at raising the proportion of women graduating from science-related fields and entering the labour market.

Favourable business policies are critical to ensure technology is adopted broadly. Ensuring access to capital, flexible employment protection legislation and high levels of competition (e.g. by lowering administrative burdens on start-ups so they can compete with established firms), can support workers' mobility and risk-taking by firms, which in turn can promote the adoption and diffusion of digital technologies. As outlined in other chapters, policies that encourage the development and use of skills also form an important lever for the adoption of technology (Andrews, Nicoletti and Timiliotis, 2018[52]).

Labour market policies play a key role in countries' capacities to make the most of digital transformation, as they influence not only innovation and technology adoption but also skills development and use. Flexible employment protection legislation (EPL) can facilitate labour market restructuring and the adoption of new technologies. A large share of temporary contracts and high labour market mobility can be less conducive to innovation, however, which requires time and stable teams.

At the same time, EPL affects how much training employers provide. Recent evidence from Finland and Italy suggests that a higher reliance on temporary contracts diminishes employer-sponsored training (Bolli and Kemper, 2015[84]; Bratti, Conti and Sulis, 2018[85]). The digital transformation may further promote the diffusion of non-standard forms of work, which may reduce job security for some workers and limit access to training. Countries need to reassess their labour market policies to take into account the range of implications of the digital transformation on labour markets.

Several countries seek to boost their competitive edge in the technology sector by attracting highly skilled migrants to alleviate labour shortages or build human capital. France, Israel and Korea have all recently introduced "tech" visas with expedited procedures (OECD, 2018[86]). To ensure highly skilled migrants can contribute to the host country's skills pool, policies need to align the migration system with longer-term economic development policies as well as immediate labour needs, and put systems in place that assess and recognise qualifications and skills (Papademetriou, Somerville and Tanaka, 2008[87]).

Economic development policies at national, regional and local levels play an important role in realising the potential of digitalisation. Such policies need to be multifaceted. They include developing the business environment, boosting education and skills and infrastructure, and developing regions' competitive advantages through clusters that combine economic activity with research, development and innovation in key sectors. Policies that boost international trade and investment are also vital (OECD, 2018[88]). Co-ordinating economic development policies with education and skills policies is crucial to ensure the right levels and types of skills are available to meet economic needs at national, regional and local levels. An insufficient supply of skilled workers can limit a country's or region's ability to build strong competitive advantages in global value chains, while insufficient demand for skills can spur outward migration to other regions or countries.

Tax policies can play various roles in the digital economy. First, they influence the incentives of individuals and firms to work and hire, and the incentives of both to invest in skills. For instance, in systems where a high portion of increased earnings expected to result from training are taxed away, incentives to increase skills may be lower. Motivations for increasing skills are broader, however, and can depend on other policies, such as social and labour market policies. As a result, it is vital to co-ordinate education and training policies with tax, social and labour market policies.

Second, a key role of tax systems is to lower the gap between market income and disposable income through redistribution. However, the digital transformation may amplify existing skills disparities within socio-economic, gender and age groups, as some groups are less likely to retrain, learn about new skills in need, and make informed career choices. These increased skills disparities may translate into higher wage inequalities, making it more costly to correct market income inequalities through tax policies (OECD, 2017[89]; Berger and Frey, 2016[45]). Thus, investing in skills, especially to provide high quality education to all, is needed not only to achieve inclusive growth but also to ensure that tax policies are effective.

Social protection policies, along with taxation, are a major policy instrument to help workers move smoothly between jobs or deal with job displacement or unemployment spells. They can also prevent new forms of work from pushing workers into lower-quality jobs. The rise of the platform economy obliges governments to identify the best ways to provide opportunities for workers to improve their skills, as well as sufficient protection for vulnerable workers who may not have access to health or retirement benefits. In addition, policies should make social security entitlements portable so that workers do not lose benefit entitlements when they move between jobs. Re-thinking social protection systems also requires a co-ordinated approach, to ensure social benefits are combined with effective tax systems and labour market policies, and open and flexible lifelong learning systems.

Housing and transport policies are critical to facilitate workers' mobility and their access to work opportunities, and thereby prevent the digital transformation from exacerbating geographical inequalities.

Table 6.1 Policies for digitalisation

Policies	Relevance: Does the policy promote the benefits of digitalisation, address risks, or both?		What are connections and complementarities between policies?	What stakeholders are most affected by these policies and should be engaged by government?
	Promotes benefits	Mitigates risks		
Digital infrastructure, innovation, technology adoption (in firms and government)	X		Changes demand for skills in all sectors (private sector, government and public services) Requires adapting to new forms of firms and work (scale without mass, no footprint)	Firms Particular focus on SMEs who lag behind in digital technology adoption
Business environment, competition (ease of entry and exit), access to capital	X		Changes demand for skills Accelerates innovation and take-up of technology	Firms Particular focus on firms in sectors with high barriers to entry, e.g. low access to capital
Migration policies	X		Supplements national skills supply Fosters digital technology adoption, innovation, business creation, regional and local development	Employer associations Unions
Lifelong learning (education and skills), managerial quality	X	X	Increases supply and demand of skilled workers to the labour market, accelerates adoption of digital technology and innovation, creation of businesses, attractiveness of country for foreign investment, regional and local economic development Increases tax revenues Can lower need for social protection	Firms Unions Education and training providers Employment and social services to reach low-skilled

Labour market policies and institutions	X	X	Flexible policies facilitate mobility of workers matching of skills to jobs, and in turn improve economic development, digital technology adoption, innovation and business creation, and increase tax revenues Can increase skills investments by employers and engagement in lifelong learning of individuals Can lower need for social protection	Firms Unions Education and training providers Employment and social services to reach low-skilled
Economic development and industrial policy (at all levels: foreign investment in countries, regional & local development)	X	X	Increases demand for skills and improves opportunity for labour-market relevant skills development opportunities locally Increases digital technology adoption, innovation, business creation Can increase tax revenues Can lower need for social protection	Firms Employer associations Education and training providers Employment and social services
Tax policies	X	X	Can stimulate skills investments, investments in technology, innovation and business creation Complement social protection via redistribution mechanisms	Firms Unions
Housing and transport	X	X	Facilitates worker mobility and better allocation to jobs; can lower need for social protection	Firms Unions
Social protection		X	Supports return to labour market, lifelong learning and upskilling if well connected with these policy areas	Firms Unions Representative of workers in the gig-economy not covered by unions

Sources: Based on information from OECD (2017[81]), *OECD Science, Technology and Industry Scoreboard 2017: The Digital Transformation*, https://doi.org/10.1787/9789264268821-en (accessed on 02 August 2018); Andrews, D., G. Nicoletti and C. Timiliotis (2018[52]), "Digital technology diffusion: A matter of capabilities, incentives or both?", http://dx.doi.org/10.1787/7c542c16-en; OECD (n.d.[90]), *OECD Skills Strategy 2019: Skills to shape a better future*, https://doi.org/10.1787/9789264313835-en.

Policy complementarity and whole-of-government co-ordination

Given the linkages between various policies necessary to make the most of digitalisation, countries need to co-ordinate the implementation of policy "packages" to ensure these have mutually reinforcing effects. Without co-ordination, there is a risk that policies fail to deliver results. This risk has been demonstrated by evidence that technological innovation does not lead to increased productivity if other policies are not in place, such as labour market policies, education and skills policies and a conducive legal framework (Acemoglu and Zilibotti, 2001[91]; Andrews, Nicoletti and Timiliotis, 2018[52]).

The geographical dimension of the digital transformation reflects a myriad of dynamics that can be influenced by policies at the national and local levels. In addition, a good understanding of the local context is often crucial to ensure the effectiveness of interventions (Rodríguez-Pose and Wilkie, 2017[92]). Actors at all levels need to co-ordinate policymaking across a wide range of areas, including education, housing, mobility, innovation, taxation and transportation. This co-ordination should focus on how each policy domain can mutually reinforce the effects of other domains in order to maximise the impact on regional development.

Policies

Along with significant public investments, governments are taking various approaches to co-ordinating complex policy packages. One key strategy consists of setting up governance structures responsible for monitoring the integrated design and co-ordinated implementation of multi-faceted strategies, such as national digital agendas.

The governance mechanisms used by countries are diverse (Table 6.2). Despite the high importance of the digital agenda and the breadth of policies that need to be involved, in most OECD countries national digital strategies are developed by a single ministry or body that is not located within the centre of government, and other ministries are mostly included solely for the implementation of policies. Such arrangements may hinder countries' abilities to co-ordinate and align policies, and make the most of the digital transformation.

Table 6.2. Governance of national digital strategies

	Lead the development	Contribute input	Co-ordinate	Implement	Monitor
Government, e.g. Prime Minister's Office, Presidency, Chancellery, Ministerial Council	4	0	5	1	6
Digital affairs ministry or body or ministerial position	8	1	10	3	8
Ministry or body not dedicated to digital affairs	15	2	13	1	11
Several ministries, bodies or institutions	6	14	5	26	7
Multiple public and private stakeholders	1	17	0	3	0

Source: OECD (2017[81]), *OECD Digital Economy Outlook 2017*, http://dx.doi.org/10.1787/9789264276284-en.

Another, often complementary, approach consists in establishing clear indicators of performance to measure the success of the digital strategy. Across the OECD, commonly used indicators include expanding broadband infrastructure; improving e-government and services; raising the use of Internet, online services, and digital technologies; increasing e-commerce and digitalisation of businesses' and improving citizens' skills in ICT and more broadly (OECD, 2017[81]). While these indicators are broad, they may not fully capture the whole range of areas that would need to be integrated into such strategies.

Only a few countries – Austria, Luxembourg, Mexico and the Slovak Republic – reported having as the lead for their national digital strategies a single high-level government official, e.g. in the Prime Minister's Office, Presidency or Chancellery, or a ministry or body dedicated to digital affairs. In Luxembourg and Mexico, the leadership of government in integrating a digital perspective in different policy areas has led to positive results, ranging from greater coverage of digital infrastructure to the improved use of digital technologies by citizens. Denmark has introduced a Disruption Council chaired by the prime minister, following its tradition of discussing transversal policy issues through commissions gathering the government, experts, employers and employees' organisations (Box 6.3).

Finally, implementing multi-faceted reforms requires taking into account the political economy of factors that can support or hinder the success of reform. This includes carefully analysing and planning the reform (which often involves significant time), engaging stakeholders while showing cohesive government leadership, and explaining to everyone involved the benefits of reform and the cost of not changing the status quo (Tompson, 2009[93]).

Box 6.3. Co-ordinating policies in the digital age

Created in 2014, **Digital Luxembourg** is an initiative that involves ministries, researchers, innovators and companies, and reports directly to the prime minister. Digital Luxembourg identifies needs and co-ordinates support for digital innovation. It offers support through financial investment, endorsement of projects, and a web platform and outreach activities that raise awareness about digital initiatives in the country.

The initiative supports progress in five priority areas: (i) improving skills, with projects such as coding in schools or women in tech, (ii) developing a digital ecosystem, with a EUR 20 million digital tech fund investing in a range of areas, from ICT startups to digital security, (iii) policy, with a focus on open data and privacy regulations, (iv) e-government, and (v) digital infrastructure, including broadband, free wifi, artificial intelligence and blockchain projects.

Luxembourg is among the top performers in the European Union's Digital Economy and Society Index (DESI). It ranks highly in human capital, in particular the use of digital skills and the Internet. Since its creation, Digital Luxembourg has enabled projects ranging from machine-readable legislation to new skills training opportunities.

Mexico's National Digital Strategy was created in 2013 and is led by the Co-ordination of the National Digital Strategy (NDS), an entity within the Executive Office of the president. The strategy aims to spur the development and adoption of digital technologies as part of achieving the goals of Mexico's National Development Plan.

The NDS focuses on: (i) government transformation, (ii) the digital economy, to boost innovation and productivity, (iii) education and skills, (iv) expanding access and quality of health services, and (v) civic innovation and citizen participation. Key policy initiatives focus on digital infrastructure, developing and using digital skills, the interoperability of government services, improving the legal framework governing the use of ICTs, and promoting open data.

Mexico has made notable progress towards a digital society. The 2017 OECD OUR (Open, Useful, Reusable) data index places Mexico at 5th place, after Korea, France, Japan and the United Kingdom, up from 10th in 2014.

In 2017, the **Danish government** established a **Disruption Council** to analyse, debate and present proposals for how Denmark should take advantage of the opportunities that technology brings. The council is chaired by the prime minister and includes several relevant ministers, as well as companies, trade unions, business leaders, entrepreneurs, experts and representatives from the rest of society. The council has already discussed and provided input to a tripartite agreement on a stronger and more flexible system for continuing training. In addition, the council contributed to the Danish government's digital strategy, which was launched in January 2018.

Sources: Digital Luxembourg (2018[94]), *Progress Report. Spring 2018*, https://digital-luxembourg.public.lu/sites/default/files/2018-06/DL_201804022_PROGRESS%20REPORT_08%20BAT.pdf (accessed on 03 August 2018); European Commission (2018[95]), *Digital Economy and Society Index 2018, Country Report Luxembourg*, https://ec.europa.eu/digital-single- (accessed on 03 August 2018); Coordination of the National Digital Strategy (2016[96]), *Mexico: The National Digital Strategy. An Action Plan for a Digital Country, Background Paper*, https://www.intgovforum.org/cms/igf2016/uploads/open_forum_background_paper/Mexico_Open_Forum.pdf (accessed on 03 August 2018); OECD (2018[97]), *Open Government Data in Mexico: The Way Forward*, https://doi.org/10.1787/9789264297944-en (accessed on 03 August 2018); Danish Ministry of Employment (2017[98]), *Disruptionrådet*, https://bm.dk/arbejdsomraader/aktuelle-fokusomraader/disruptionraadet/ (accessed on 28 August 2018).

Summary

This chapter considers two important objectives of policies intended to make the most of the digital transformation: 1) they need to foster lifelong learning, which is critical for workers and citizens adapt to changing world of work and societies, and 2) they need to facilitate mutually reinforcing local beneficial effects of skills and technology. If policies fail to achieve these objectives, the digital transformation may increase inequalities between individuals. Inequalities in learning opportunities often start in early childhood education, fuelled by differences in socio-economic background and the places people live. These inequalities are reinforced in schools and higher education, and continue into the labour market, where low-skilled workers have fewer opportunities to train and face greater risk of losing their jobs, especially in regions where industries are exposed to automation and few high-tech firms are creating jobs.

A well co-ordinated package of policies, centred on education and skills measures, is needed to foster lifelong and country-wide learning and more generally to ensure the digital transformation improves lives and livelihoods for all. A significant policy effort is required because of the range of policies that need to be better co-ordinated, the need to put in place structures and mechanisms to support this effort and the complexity of the inter-relations between policy areas.

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