Skills for the Digital Transition

ASSESSING RECENT TRENDS USING BIG DATA

OECD

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BETTER POLICIES FOR BETTER LIVES

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Foreword

New digital technologies, including artificial intelligence, robotics and information and communication technologies are reshaping the way people live, work and learn. These new technologies can enhance the way people learn, where, when and how they work, and spur their engagement in society by extending everyone's ability to gather, interpret and analyse information and communicate with others around the globe seamlessly.

While technologies are constantly evolving, those changes are poised to replace some of the tasks in jobs that are currently carried out by humans and, in turn, freeing time to produce more innovation, eventually leading to further changes and even more radical shifts in the way humans interact with machines in society and labour markets. This report presents the most recent trends in the demand for digital occupations using the information contained in millions of job postings collected from the internet. Results highlight where labour market bottlenecks are emerging and policy action is – and will be – needed to support individuals to acquire digital skills to thrive in rapidly evolving labour markets and societies.

The report is organised as follows: Chapter 1 provides an overview of the main results of the report. Chapter 2 presents the new challenges for the labour market and the demand for digital skills. Chapter 3 discusses the data that underpin the analysis, providing details on how job postings are collected from the internet and processed using machine learning techniques. The chapter also discusses the representativeness of the data, its advantages and limitations in the context of the current analysis. Chapter 4 analyses the evolution of online job postings at the deepest occupational disaggregation level available in job postings, by focusing on a selection of key digital occupations across different sectors and countries. The analysis compares the evolution of the demand for workers in occupations within the same country while also providing a cross-country snapshot showing differences in the demand for digital occupations across the geographies covered in the report. Chapter 5 uses novel machine learning techniques to analyse the skill information contained in the text of online job postings in order to assess the relevance of new technologies, digital tools and skills for the digital occupations covered in this report. Chapter 6 assesses the diffusion of digital skill demands over time by investigating the speed with which a variety of digital technologies have been permeating labour markets over time. The analysis compares the diffusion of digital skills with the average of the economies under consideration with the intent of identifying areas where the demand for digital skills and technologies have been particularly strong across the countries analysed. Chapter 7 concludes the report by leveraging the granular information on skill demands at the occupation level to compare the skill profiles of occupations in decline with those of occupations that are growing in the labour market and to suggest potential the key skill needed to retraining and move from traditional jobs to thriving digital ones.

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Executive summary

The adoption of digital technologies is enhancing the way people learn, where, when and how they work, and spurring their engagement in society. This report reviews the evolution of a wide selection of digital occupations using a unique set of data collected from job postings published online.

This report presents the most recent trends in the demand for those digital occupations, highlighting where labour market bottlenecks are emerging and policy action is – and will be – needed to support individuals to acquire digital skills to thrive in rapidly evolving labour markets and societies. The granularity of the information used in this report enables to identify the specific skill demands of employers in each country and to support the design of labour market, education and training policies to respond effectively to current and forthcoming challenges. This report also targets the general public, by providing insights on the direction taken by labour markets and on what workers may need to expect in terms of skill demands in the near future so that their education and training decisions can be informed by knowledge of these recent trends.

This report focuses on Belgium, Canada, France, Germany, Italy, the Netherlands, the United Kingdom, the United States, Singapore and Spain.

Among the digital occupations analysed, software developers, programmers and engineers, data scientists and data engineers have experienced some of the most notable rates of growth in most countries. In Canada, for instance, the number of job postings for user interface and user experience (UI/UX) designers was more than three times larger in 2021 than in 2012. Similarly, in the United Kingdom, the demand for UI/UX designers reached its all-time peak in 2021, with almost 15 000 new job postings published online in one year.

In most EU countries, information on online job postings (OJPs) is only available for a relatively shorter time span and at a higher aggregation level. Evidence for EU countries shows that job vacancies for digital professionals have been negatively affected by the strong decline in economic activity experienced during the COVID-19 pandemic. Despite this, even during the pandemic, some digital occupations have experienced a marked increase in the volume of vacancies relative to the pre-pandemic period in the EU. In Italy, for instance, the number of OJPs for database and network professionals increased nearly nine times between 2014 and 2021, reaching more than 2 000 new vacancies per year. Looking forward, the demand for many digital professionals in the EU is foreseen to grow in the medium to long term, as the effects of the COVID-19 pandemic on labour markets are fully absorbed.

Evidence in this report also shows that digital jobs require a heterogeneous mix of technical and high-level cognitive skills. Results show, for instance, that database management skills are demanded by employers along with several other data-related and data analytics skills. Similarly, the analysis uncovers recent trends in the skill demands of digital occupations such as the increasing relevance of open source platforms and the knowledge of programming languages such as Java.

More generally, results show that advanced data analysis skills such as the knowledge of machine learning, data science and data visualisation are at the core of the development and adoption of a variety of different digital technologies that leverage the use of the available digital data.

Evidence in this report also confirms the strong increase in the demand for social media skills in labour markets as a whole and not only in occupations that are digital, suggesting that an increasing number of businesses are now hiring (or searching for) workers with skills in the area of social media management.

Finally, this report uses OJPs to identify the skill similarities between occupations and to determine what type of retraining would be needed to make a career transition from occupations whose employment projections are negative to others that are instead expected to grow in the future and that are digital in nature.

Results show, for instance, that workers in "traditional" jobs such as advertising sales agents could retrain to become digital marketing specialists by acquiring training in the area of web analytics, online marketing, search engine optimisation (SEO), copywriting and related technical skills such as Semrush. Other retraining pathway examples are provided in the report.

The evidence contained in this report is key for governments to design targeted retraining and upskilling policies and for workers to benefit from the digital transition, thus supporting countries and individuals to thrive in future labour markets.

1 Overview of labour market and skill demand trends in digital occupations

This chapter discusses the main results of the report by giving a short overview of the trends in the demand for digital professionals across the countries covered in the study: Belgium, Canada, France, Germany, Italy, the Netherlands, the United Kingdom, the United States, Singapore and Spain. The chapter also provides a summary of the results, presented in this report, that quantify the pace by which the demand for digital skills has been diffusing across occupations in recent years. Finally the chapter briefly discusses how big data and the information contained in millions of job postings collected from the internet can be leveraged to build targeted retraining pathways to inform upskilling and retraining policies for workers employed in declining occupations to move in jobs in high-demand.

1.1. Digital technologies, including artificial intelligence and robotics are reshaping the way people live, work and learn

The adoption of digital technologies is enhancing the way people learn, where, when and how they work, and spur their engagement in society. The overall impact of technology adoption on labour markets is expected to be positive but anxieties remain as to whether technology may increase some of the existing divides as individuals who lack adequate skills are likely to face barriers to remain engaged in labour markets that will increasingly require digital skills.

This report focuses on a wide selection of digital occupations such as computer and data analysts or administrators, software developers, programmers and engineers, ICT technicians and data entry clerks as well as ICT and HR managers and marketing specialists.[1] The report also provides insights focusing on the adoption of digital technologies, tools, software programmes in jobs and labour markets more generally.[2]

The insights contained in this report are key for policy makers to understand the profound changes that the digital transition is bringing across labour markets and to anticipate further changes in an effective manner. These insights are also central to spur the debate on the design of effective reskilling and upskilling pathways for all workers to benefit from digitalisation. Evidence in the report presents the most recent trends in the demand for digital occupations, highlighting where labour market bottlenecks are emerging and policy action is (and will be) needed to support individuals who want to acquire digital skills to thrive in future labour markets and societies. The granularity of the information used in this report allows to identify the demand of employers in each country and to support the design of precise labour market and education policies respond to current and forthcoming challenges. This report also targets the general public, by providing insights on the direction taken by labour markets and on what workers may need to expect in terms of skill demands in the near future so that their education and training decisions can be informed by their knowledge of these recent trends.

1.2. The demand for digital professionals has increased significantly, but the pandemic has also hit some digital occupations

The evidence presented in this report shows the significant increase in the number of job postings published online for a wide range of digital occupations while also showing the negative impact that the COVID-19 crisis has had across all labour markets and, as a consequence, on some digital professions.

Vacancies published online for data engineers and data scientists in Canada, the United Kingdom and the United States, for instance, experienced a striking growth in recent years with OJPs for data scientists increasing by more than 40 times in between 2012 and 2021.

Among digital occupations, software developers, programmers and engineers have also experienced some of the most notable rates of growth. In Canada, for instance, the number of job postings for User interface (UI), User experience (UX) designers or developers engineers (in charge of the design of user interfaces for machines and software, such as computers, home appliances) was, in 2021, more than three time larger than in 2012. Similarly, in the United Kingdom, the demand for UI / UX designers / developers reached its all-times peak in 2021, with almost 15 000 new job postings published online in one year.

In EU countries (with few exceptions), information on OJPs is only available starting in 2018. Results over this relatively shorter time span (if compared to non-EU countries where information is available starting in 2012 and with a higher granularity level) show that job vacancies in the EU countries have been heavily affected by the strong declines in economic activity experienced during the pandemic. Despite that, even during the pandemic, some digital occupations have experienced an increase in the volume of vacancies relative to the pre-pandemic period. For instance, in Italy and France, job postings for database and network professionals have increased steadily since the start of the available time series in 2018. In Italy, in particular, the number of OJPs for those professionals increased by nearly 9 times over the period considered while in other EU countries such as Belgium, Germany, the Netherlands or Spain the demand for database and network professionals reached its peak in 2019 but then declined as the COVID-19 crisis hit. Despite the drop during the COVID-19 crisis, demand for many digital occupations in the EU is still expected to increase in the medium to long-run as a result of further adoption of digital technologies.

1.3. The rapid pace of the digital transformation is reshaping the skills that are required to perform jobs and tasks within digital occupations

Evidence in this report shows that digital jobs require a heterogeneous mix of technical and high-level cognitive skills to be performed. Results show, for instance, that database management and warehousing skills are required with several other data-related and data-analytics skills. An emerging trend in the skill demands of digital occupations is the increasing relevance of open source platforms and of software libraries such as Tensorflow (an open-source platform that allows to operate machine learning and artificial intelligence in a variety of different contexts). Similarly, the knowledge of programming languages is key in a variety of upward trending digital jobs. The knowledge of Java is, for instance, particularly relevant for software developers and programmers in Germany.

It is well known that digitalisation is intertwined with automation in that automation relies on the use of digital technologies to monitor processes and collect data to optimise production. Among other results, the evidence in this report shows that computer-aided engineering (CAE) software are key for electronics engineers and ICT operations technicians in several EU labour markets among which Belgium and Germany. Across jobs analysed in this report, technical expertise in using CAE is also commonly required along with the ability to use technical drawing software and joint with the knowledge of automation technologies and of the internet of things (IoT).

Interestingly, business and sales-related skills are key for a subset of software-related occupations such as web designers. Results for the United States, for instance, show that web developers are typically required to know about online advertising and online marketing. Web analytics are also very relevant for web designers in Singapore while the knowledge of copywriting is demanded in jobs for web designers in Canada.

1.4. The penetration of digital technologies and skill demands has increased exponentially in a variety of different sectors of the labour market, going from mechanics and manufacturing to services and health care

The analysis of the keywords mentioned in job posting published online allows to ascertain how widespread digital skills and technology demands are becoming across a variety of different occupations and the pace by which their use is spreading across jobs. Metrics presented in this report analyse millions of job postings looking for trends in the demand for digital skills comparing them with the average dynamics of each labour market in order to determine whether the demand for digital skills has been growing faster than that of the average skill in each labour market.

Results show that advanced data analysis skills such as the knowledge of machine learning, data science and data visualisation are at the core of the development and adoption of a variety of different digital technologies that leverage the use of the available digital data. Evidence for the United States and Canada, for instance, shows that the speed by which advanced data analysis skill demands have diffused across occupations is in between 10 to 15 times faster than for the average skill in each of those labour markets respectively.

Results also show that the demand for programming skills, among which JavaScript or Python, has been spreading across occupations in the United States and the United Kingdom at a particularly rapid pace (in between 6 and 9 times faster than the diffusion of the demand for the average skill in online job postings). Technical expertise and knowledge of Ubuntu, an open source Linux-based operating system designed for computers, smartphones, and network servers is among the digital competencies whose demand have diffused faster across occupations in EU countries in between 2018 and the end of 2021, in particular in Belgium, France and the Netherlands.

Interestingly, the knowledge of automation and of IoT is becoming increasingly important in production processes. Results in this report seem to suggest that the demand for skills in those areas is still relatively concentrated in a narrower set of jobs if compared to other types of digital skill demands.

Evidence in this report also confirms that the uptake of social media has been fast in the period between 2012 and 2021. The demands for social media skills has diffused across occupations up to 14 times faster than the average in the United Kingdom and in the United States, suggesting that an increasing number of businesses are now hiring (or searching for) workers with skills in the area of social media management.

1.5. In today’s rapidly-changing labour market, one key challenge lies in ensuring that workers are able to move from declining occupations to other jobs that are expected to thrive in rapidly changing labour markets

While technological change is among the drivers of the possible decline in employment in some occupations, digitalisation represents also an opportunity for many workers to develop new skills and transit to different career paths that are digital in nature and that are expected to thrive in future labour markets.

The information contained in online job postings is used, in this report, to identify the skill similarity between occupations and to determine what type of retraining would be needed to make a career transition from occupations whose employment projections are negative to others that are instead expected to grow in the future.

By leveraging the skill information contained in OJPs the report shows, for instance, that workers in “traditional” jobs such as advertising sales agents could retrain to become digital marketing specialists by acquiring training in the area of web analytics, online marketing, SEO Copywriting and related technical skills such as Semrush. Other examples of retraining pathways are provided in the report for Satellite/broadband technicians to move into Computer support specialists’ careers or from customer service managers to data engineers. These examples, and others that could be built using the information in OJPs, can inform the work of public employment services to support the design of short and targeted retraining and upskilling courses for workers in occupations at risk of automation.

Reference

Randstad Research Italy (forthcoming), *Connessioni al servizio della fruibilità. Le 100 e più professioni digitali del futuro*. [1]

Notes

[1] Chapter 4 discusses the full list of digital occupations analysed in this report. Digital occupations have been selected based on the degree by which workers interact with digital tools, technologies or produce/use digital content. The final selection of digital occupations has also benefitted from input by experts in Randstad Research Italy and the companion study “Connessioni al servizio della fruibilità. Le 100 e più professioni digitali del futuro” (Randstad Research Italy, forthcoming[1]).

[2] The text of job postings published online contains mentions of digital technologies, tools, software and skills. In this report, for ease of presentation, those keywords will be grouped under the label of “digital skills” unless the distinction between them is useful to present and highlight specific results.

2 The new challenges for the labour market and the demand for digital skills

This chapter sets the scene for the report by discussing the impact that the digital transition is having on labour markets. The chapter discusses previous empirical evidence that looked into the adoption of digital technologies in jobs and how the adoption of new technologies is reshaping labour market and skill demands. The chapter also briefly reviews the available evidence, produced using online job postings, on the impact of COVID-19 on labour market trends in light of the surge of teleworking. Finally, the chapter discusses some of the most prominent studies that have analysed the impact of digitalisation on the risk of automation and, in turn, on labour markets and employability of workers of all skill levels.

New digital technologies, including artificial intelligence, robotics and information and communication technologies are reshaping the way people live, work and learn. It is nowadays clear that digitalisation presents an immense potential to boost productivity and improve the well-being of all individuals around the world but concerns remain as to whether the digital transition and the future of work will be inclusive for all individuals (OECD, 2019[1]).

While technology is constantly evolving, those changes are poised to replace some of the tasks in jobs that are currently carried out by humans and, in turn, freeing time to produce more innovation, eventually leading to further changes and even more radical shifts in the way humans interact with machines in society and labour markets.

The adoption of new digital technologies can enhance the way people learn, where, when and how they work, and spur their engagement in society by extending everyone's ability to gather, interpret and analyse information and communicate with others around the globe seamlessly.

Much of these new opportunities are nowadays made possible by the exponentially increasing computing power of digital devices which allows the development and implementation of a range of new digital technologies such as 3D printing, the Internet of Things (IoT) or advanced robotics.

Digital infrastructures and the access to devices such as smartphones has grown, from 4% to 40% of the world's population in 20 years (OECD, 2017[2]) and interconnected digital devices are used today to collect and distribute big-data from (and to) final users which are then used to optimise all steps of production. The penetration of these new technologies in production as well as in the service sector is showing already substantial repercussions on the way jobs and tasks are carried out.

Some of the areas where digital technologies found significant application are in the production of goods and the delivery of services. As for the former, the introduction of digital technologies in production led to the emergence of the so called "*Industry 4.0*" (I4.0), or the fourth industrial revolution. The term I4.0 refers to the use in industrial production of interconnected digital technologies that allow processes to be more efficient, timely and cost-saving.[1] Among the various digital technologies used in the I4.0 there are the recent developments in machine learning and data science (which allow operating increasingly autonomous and intelligent systems with little or no supervision) to physical sensors that collect and process information that is key to operate the Internet of Things (IoT) and that make second-generation industrial robotics possible.

Among the reasons of their success in industrial production is the fact that machine downtime and repair costs can be greatly reduced when intelligent systems predict maintenance needs. Similarly, significant savings can be had if industrial products can be simulated before being made, and if industrial processes can be simulated before being implemented. Data-driven supply chains greatly speed the time to deliver orders and digital technologies can allow production to be set to meet actual rather than projected demand, reducing the need to hold inventories and lowering failure rates for new product launches (OECD, 2017[2]).

These new trends are becoming increasingly widespread and are affecting parts of the labour market that were not traditionally deemed to be "digital" in the past. Cargo-handling vehicles and forklift trucks, for instance, are nowadays increasingly computerised. Many semi-autonomous warehouses are populated by fast and dexterous robots and complex aspects of the work of software engineers can be performed by algorithms (Hoos, 2012[3])

Digital tools can now replace workers in several routine tasks and even complement workers in tasks that require creativity, problem solving and cognitive skills. The ability of digital technologies to perform some routine tasks led to the vast increase in their use within the service sector. The collection and use of personal information and geolocalised data is used by firms to advertise or tailor their own products in areas like the e-commerce, banking and health.

Just as a matter of example, IBM's Watson computer can act as a customer service agent (Rotman, 2013[4]) while the Quill programme writes business and analytic reports and Automated Insights can draft text from spreadsheets. Computer-based managers are being trialled. These allocate work and schedules, with the experience well received by teams of workers to date (Lorentz et al., 2015[5]). Recent software can interpret some human emotion better than humans, presaging new forms of machine-human interaction (OECD, 2017[2]).

The development of new digital technologies powered by Artificial Intelligence (AI, henceforth) occupies a particularly important space in the policy debate that focuses on the impact that digital technologies will have on labour markets. An increasing number of scholars – see for instance (Aghion, Jones and Jones, 2017[6]; Brynjolfsson, Rock and Syverson, 2017[7]; Fossen and Sorgner, 2019[8]) – have adopted the view that AI should be regarded as a General Purpose Technology (GPT) whose fundamental characteristic is that of being able to improve (and self-improve) over time, solving complex problems and generating complementary innovations with little or no human supervision.

In the workplace, the adoption of digital technologies is contributing to a new wave of AI-powered automation. Algorithms are taking on more and more routine tasks, displacing workers from some traditionally cognitive jobs. Muro, Whiton and Maxim (2019[9]) argue for instance that AI is making significant progress in replicating a particular aspect of intelligence, namely "prediction", this latter being central to decision making and an essential aspect of high-skilled jobs in the health care or business sector. Similarly, (Felten, Raj and Seamans, 2019[10]) and (Webb, 2019[11]), stressed AI's ability to perform non-routine cognitive tasks through their ability to autonomously "acquire" and "apply" knowledge in problem solving contexts.

New examples, showing the ability of AI to perform such tasks, are being developed at a fast pace. GPT-3 is, for instance, one of the most sophisticated AI-powered Natural Language Processing (NLP) algorithm to this date. The current version of GPT-3 is able to answer complex medical questions and to identify correctly a disease from the simple description of its underlying symptoms, even suggesting the necessary treatment for the disease at hand. Notably, GPT-3 capabilities are transversal, ranging from its ability to write new software code to that of programming mobile applications or to produce autonomously poems and journal articles when prompted with a few lines of text.

2.1. The labour market and the COVID-19 pandemic: What role for digital technologies?

Digital technologies played a fundamental role also during the recent COVID-19 pandemic. Evidence (OECD, 2021[12]) shows that the rapid adoption of digital technologies during the coronavirus pandemic has helped protect the jobs of millions of workers who were able to carry out their activities remotely and working from home. The COVID-19 crisis obliged many firms to rethink the way they were doing business and to adjust to a "new normal" where little or no physical interaction was allowed both among co-workers as well as with customers.

As the availability of human manual labour decreased dramatically due to social distancing measures, many firms started adopting new and automated ways to connect with customers. Cashierless stores in the retail sector are a clear example of this trend. Amazon's checkout-free shopping experience, for instance, leverages a similar technology as the one used in self-driving cars (computer vision, sensor fusion, and deep learning) to automatically detect when products are taken from or returned to the shelves, keeping track of them in a virtual cart and allowing customers to exit the shop without having to queue at the counter before leaving, eliminating the need for cashiers or self-service checkout assistants. Sainsbury's is offering a similar service through its SmartShop system (Wallace-Stephens and Morgante, 2020[13]) which allows customers to scan their groceries as they go around the store and pay via an app. Sales from this service have reportedly increased from 15% to 30%.

While some of these new technologies were developed prior to the pandemic, the speed by which they have been adopted recently has increased considerably. To give an example, reports in the United Kingdom from the ONS Business Impact of Coronavirus Survey (BICS), indicate that almost one in three businesses have increased their use of online services to help communicate with customers since the pandemic and Sainsbury's former CEO suggested that the use of digital technologies to eliminate cashiers "might have taken three or four years to get to, [but] it happened in the space of less than six weeks" during the pandemic.

While many employers and employees have used digital technologies to weather the COVID-19 crisis, in particular by adopting teleworking arrangements, others have instead been unable to do so due to the lack of adequate skills or the necessary technological infrastructures in their workplace. This is one of the many examples of how the digital transition could create, or further widen, divides and inequality.

2.2. How will the future of labour markets look like as the digital transition unfolds?

The increasing ability of digital technologies to perform routine as well as cognitive tasks in a manner that is as effective as humans will have a large impact on the way services are delivered, products are manufactured and innovation itself is created (Autor, Levy and Murnane, 2003[14]). 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).

The fast-paced adoption of digitally powered technologies will certainly have fundamental repercussions on the type of skills that individuals will need to master in at least two separate ways. On the one hand, individuals will need to develop adequate digital and cognitive skills to interact with digital technologies. Digital tools, in fact, do not operate in a vacuum and much of their potential is determined by how well workers are able to interact with them. This is for instance the case of AI, where workers are expected to supply the correct inputs to AI-algorithms and, more importantly, to critically understand the outputs that are produced in return. In other words, individuals will need to be educated on how to detect biases, fakes and mistakes that could result from the misuse of AI.[2]

On the other hand, digital technologies are likely to replace humans in specific cognitive tasks at work, freeing up time of human labour to perform other tasks that AI is still not capable of doing effectively. Socio-emotional skills and all those traits that make us "humans" (i.e. empathy, intuition and creativity) are expected to become increasingly more important in future labour markets as AI is adopted more broadly in society and at work.

When focusing on the impact of technology on labour markets and jobs, recent research (OECD, 2019[1]) suggests that the adoption of traditional automation technologies (for instance, industrial robotics applied to narrow and repetitive tasks) has, indeed, contributed to the polarisation of skill demands where occupations using mid-level skills have been those most affected by automation due to the routine nature of their tasks.

Technologies can potentially complement and amplify human potential in combinatorial ways. Going forward, the overall impact of digitalisation on jobs will therefore depend on how much digital technologies will complement rather than substitute workers in specific tasks. Today, for example, advances in software and data science help to develop new materials and discover new drugs. In turn, new materials might replace silicon semiconductors with better-performing substrates, allowing more powerful software applications and new drugs can open up the way for novel treatments.

Despite initial fears of potential massive technological unemployment, recent evidence suggests that employment levels have been trending upwards, with the exception of the period of global financial crisis (GFC) and the recent COVID-19 pandemic. Techno-optimists argue that new digital and other technologies will raise productivity (Brynjolfsson and Mcafee, 2014[15]), and that economic history provides reasons to think that technological progress could even accelerate (Mokyr, Vickers and Ziebarth, 2015[16]). A further argument of techno-optimists is that official measures of economic growth understate progress, because they poorly capture many of the benefits of new goods and services. For example, national statistical offices usually collect no information on the use of mobile applications, or online tax preparation, or business spending on databases while the consumer surplus created by hundreds of new digital products is absent from official data (Mandel, 2012[17]).

Other studies, however, point to significant potential labour market challenges. Acemoglu and Restrepo (2020[18]) argue, for instance, that recent declines in the share of labour in national income and the employment to population ratio in the United States – e.g. Karabarbounis and Neiman (2013[19]) and Oberfield and Raval (2014[20]) support the claims that, as digital technologies, robotics and artificial intelligence penetrate the production workflows of many countries, workers will find it increasingly difficult to compete against machines, and their compensation will experience a relative or even absolute decline.

Regardless of whether the digital transition will create net employment gains, anxieties remain as to the already existing inequalities in the access and use of technology may increase in the near future if effective policy intervention does not support the most vulnerable in developing adequate digital skills.

Individuals lacking adequate skills to use new technologies are, in fact, likely to lag behind and face barriers to engage in a new digital society or in labour markets that increasingly require digital skills.

Recent empirical evidence (Fossen and Sorgner, 2019[8]) suggests that the effects of new digital technologies on employment stability and wage growth are observable at the individual level. In particular, results for the United States in between 2011 and 2018 suggest that high computerisation risk in jobs is associated with a corresponding high likelihood of switching from one occupation to another or of becoming non-employed, as well as to a decrease in wage growth.

The negative impacts are skewed towards the most vulnerable, as results point to highly educated individuals being more able than workers with lower levels of education to adapt to computerisation risk as highly skilled workers are better equipped with skills that cannot be easily automated, such as creative and social intelligence, reasoning skills, and critical thinking.

Given the current speed of technological advancement, hardship could affect workers in specific sectors in an uneven manner. The technology of driverless vehicles is a frequently commented example of such potential displacement. Taken together, just over 3 million people work as commercial drivers in 15 European Union member states. Eliminating the need for drivers could create an exceptional labour market shock (OECD, 2017[2]).

From a policy making standpoint, it is very difficult to precisely predict how new technologies might transform existing specific jobs and as such, the extent of potential raising inequalities. In the banking sector, for instance, it was long believed that automated teller machines (ATMs) would cancel the need for human tellers. While ATMs were introduced in the 1970s, in between 1971 and 1997 the share of human tellers among all workers in US banking only declined modestly, from just under 21% to around 18% (Handel, 2012[21]). Similarly, many technologies, such as big data and the IoT, have developed in a wave-like pattern, with periods of rapid inventive activity coming after periods of slower activity and vice versa (OECD, 2015[22]). Cloud computing, for example, was first commercialised in the 1990s, but by 2017 it had still only been adopted by less than one in four businesses in OECD countries (OECD, 2017[2]).

In such uncertain and rapidly changing scenario, the analysis of timely and granular information on labour market and skill demands is key to understand the extent of the impact of the digital transformation on labour markets and workers.

This report aims to unveil the most relevant labour market trends related to the adoption of digital technologies. It does so by analysing the demand for digital skills and occupations using the detailed information contained in millions of job postings that have been published online by firms and employers across 10 different countries (Belgium, Canada, France, Italy, Germany, the Netherlands, Singapore, Spain, the United Kingdom and the United States) in between the year 2012 and now.

The analysis of online job postings in this report allows to identify the major shifts in the demand for digital skills with an unprecedented level of granularity and to track the evolution of occupational demand over time up to very recent months. The report identifies the skill profiles of the most relevant digital occupations, by highlighting the emerging adoption of new technologies, tools and digital skills across a variety of job roles.

Similarly, the report uses the detailed skill information contained in online job postings to identify skill complementarities across a variety of different occupations in order to suggest potential career transitions from occupations that are in decline to others that are thriving in the digital labour market.

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Notes

[1] In using the term Industry 4.0, the contrast is made with three previous industrial revolutions. These three revolutions can only be dated approximately. They are: i) the advent of steam-powered mechanical production equipment (1780s, or thereabouts); ii) electrically powered mass production (1870s); and iii) electronically based, automated production (1960s) (although with many differences compared to the electronics of Industry 4.0, e.g. in terms of cost, size, computational power, intelligence, interconnectivity, and integration with material objects) (OECD, 2017[2]).

[2] AI has been recently used to produce so-called “deep fakes”, that is videos posted online where celebrities as well as politicians would be seen acting or saying things that never happened in reality. The degree of sophistication of these deep fakes makes them, in many cases, indistinguishable from real videos and it poses the fundamental question of educating people to detect them. Similarly, NLP algorithms such as GPT-3 have been criticised for producing content that could be gender or race biased as the text used to train the algorithm was directly downloaded from the internet without any filter and where these biases may be present in blogs and media content.

3 Online job postings as a data source to analyse the impact of digitalisation on labour markets

This chapter discusses how big data and the information contained in millions of job postings collected from the internet can be used to track the evolution of labour markets and skill demands. The chapter discusses the advantages and the disadvantages of using big data for labour market intelligence over traditional statistics. The chapter also provide a description of the natural language processing approach used to analyse the information contained in online job postings and the metrics that are produced and presented throughout the report.

Every day, millions of individuals around the globe use new technologies to search for a job. Web platforms such as LinkedIn, Monster, Indeed, ZipRecruiter or CareerBuilder aggregate the information of millions of users and firms who meet daily in this marketplace. All those platforms provide their users with an "electronic labour market" where millions of new jobs are advertised every day.

New advancements in automated web scraping technologies (i.e. the automated retrieval and storage of textual information from the internet) allow to collect the information contained in job postings that have been published online and use it to analyse trends in labour market dynamics and skill demands. The advantages of using the information contained in online job postings over traditional labour market statistics lie in its richness, timeliness and granularity (OECD, 2021[1]).

First of all, the information contained in online job postings is collected on a rolling basis, allowing to track the evolution of skills demanded by employers up to very recent months and to detect new and emerging trends as well as technologies that may be growing and in high-demand. In particular, unlike other data sources that are based on the collection of survey information that is updated only with significant lags (i.e. O*NET or ESCO), the analysis of online job postings allows to track the changes in skill demands over time, up to very recent months. The study of online job postings also allows to examine the cross-sectional variation in skill requirements within occupations where skill demands for the same occupation may vary depending on the geography analysed. Both, in turn, allow to capture the changing nature of skill demands and the heterogeneous impact of technological progress across occupations.

Second, the granularity and high volume of the information contained in online vacancies allows to move from the analysis of generic concepts such as the assessment of the demand for the "Knowledge of Informatics" (assessed in other databases like O*NET) to the estimation of the impact on labour market of much more granular and specific knowledge domains such as "Python programming" or "Web design".

This report makes use of a large database of job postings published online and collected by Lightcast (n.d.[2]). For instance, Lightcast mines and codes millions of job postings from more than 40 000 online sources daily, scraping up to 3.4 million active job postings from thousands of webpages in the United States. Similarly, in European countries, Lightcast has more than 900 scrapers/robots monitoring more than 35 000 job portals every day and collecting more than 1 million new job postings daily.

The information contained in the Lightcast database provides up to 70 different variables ranging from skill keywords contained in each job posting, qualifications and experience required to fill the job and its geographical location, the name of the firm that is advertising the vacancy as well as the type of contract (permanent, temporary) and, when available, the salary offered for the specific role advertised.

The data are presented by a unique job-identifier and the deduplication of job postings appearing in different web and career portals ensures that the same job is not counted more than once even if appearing in different web-portals. Job postings are then mapped to different taxonomies and, in particular, to the Standard Classification of Occupations (SOC) at the 6 digits disaggregation level.

Lightcast also puts considerable effort in harmonising the skills found in the job postings. For instance, skill keywords such as "teamwork" and "collaboration" are combined into "teamwork/collaboration", and words that have several accepted spellings are considered interchangeably. It is important to notice that not all keywords collected from job postings are "skills" *strictu sensu*. Many represent "knowledge areas" (i.e. Endocrinology or Mathematical Modelling), others identify the use of specific "technologies and tools" (i.e. Python or Excel) while others relate to "abilities" required to perform an occupation (i.e. Physical Abilities or Cognitive Abilities). While the distinction between these categories bears meaningful information, this study pools them together in the analysis and distinguishes between the different concepts only when appropriate. For the sake of simplicity, in the remainder of this study, the term "skills" will be used when referring to all these different dimensions globally while knowledge, abilities, technologies and tools will be used in italics to clearly distinguish between the different concepts when necessary.

Box 3.1. Knowledge, skills, abilities, technologies and tools: What is what?

Knowledge keywords refer to an organised body of information usually of a factual or procedural nature which, if applied, makes adequate performance on the job possible. Examples are keywords such as Endocrinology which, in job postings, denote the required knowledge of all different aspects related to the medical discipline related to it and to the body of information that relates to it directly.

Skill keywords refer to the proficient manual, verbal or mental manipulation of data or things. Skills can be readily measured by a performance test where quantity and quality of performance are evaluated, usually within an established time limit. Examples of proficient manipulation of things are skill in typing or skill in operating a vehicle. Examples of proficient manipulation of data are skill in computation using decimals; skill in editing for transposed numbers, etc.

Ability keywords refer to the power to perform an observable activity at the present time. This means that abilities have been evidenced through activities or behaviours that are similar to those required on the job (e.g. ability to plan and organise work).

Technology and tool keywords refer to the knowledge of and ability to utilise certain technologies in a work context. Keywords such as Python, for instance, refer to the required knowledge of that software programming language which can be applied to tasks in different occupations. Similarly, keywords such as Excel, refer to the ability of using that statistical software package in a work-setting.

In the remainder of this report, the word "skills" is used to refer to all the above dimensions, unless more precision is needed and the specific terms are, therefore, used instead.

Source: OECD (2017[3]), "*Getting Skills Right: Skills for Jobs Indicators,*" https://dx.doi.org/10.1787/9789264277878-en.

Online job postings are also mapped to different national and international taxonomies. Information for the United States is, for instance, mapped to the US Standard Occupational Classification (SOC). In the United Kingdom, information is mapped to the UK SOC taxonomy while the National Occupational Classification (NOC) is used in Canada. On top of these country-specific occupational taxonomies, in Anglophone countries analysed in this report (namely Canada, Singapore, UK and US), Lightcast provides an overarching proprietary occupational taxonomy that allows the easy comparison of statistics computed at the occupation level across those countries.

The International Standard Classification of Occupations (ISCO) is, instead, used to classify European countries' job postings. Lightcast, however, does not provide a cross-walk between its proprietary occupational taxonomy (for Anglophone countries) and ISCO (for EU countries) so that this report, when analysing statistics at the occupation level, will refer to both the Lightcast taxonomy as well as to ISCO when applicable.

The use of different occupational taxonomies can create some challenges when comparing statistics across Anglophone countries[1] (using Lightcast occupational taxonomy) and European countries (using the ISCO taxonomy).[2] This report tries to minimise these issues by selecting occupations that are relatively comparable to each other across taxonomies. For instance, Chapter 3 analyses "database administrators" in Anglophone countries using Lightcast taxonomy at the 8th digit disaggregation level and "database designers and administrators" in EU countries using the ISCO taxonomy at the 4th digit disaggregation level. The two occupations are logically comparable, but the statistics for the latter are presented at a higher level of aggregation, meaning that more job roles may be contained therein than in the corresponding case for countries using Lightcast taxonomy.

This is also to say that the highest level of granularity in the Lightcast occupational taxonomy allows to go deeper into the analysis of smaller-sized and more detailed occupations relative to ISCO. This certainly enriches the analysis but it also calls for caution when comparing the statistics of some of the smaller-sampled occupations (in Lightcast taxonomy) with those of occupational groups that encompass more job roles (in ISCO) and that may pool together a larger number of job postings.

While the wealth and granularity of skills and labour market information contained in online vacancies is unprecedented, caveats and limitations to the use of this data also exist. First, not all job adverts are actually published online and therefore statistics therein may not be representative of the whole labour market and of "off-line" job openings. As pointed out by (Hershbein and Kahn, 2016[4]) vacancies appearing online are likely to be skewed towards certain areas of the economy despite the fact that available jobs have been increasingly appearing online instead of in traditional sources, such as newspapers. On these regards, (Carnevale, Jayasundera and Repnikov, 2014[5]) estimate that around 80-90% of postings requiring at least a Bachelor's degree can be found online, whereas 40-60% of job postings requiring a high school degree are channelled through the internet. That being said, (Hershbein and Kahn, 2016[4]) also suggest that when comparing the relative frequency of postings in online vacancies data to survey-based data online vacancies, online vacancy data reflect labour demand reasonably well and that the differences that emerge appear relatively stable over time. Recent OECD studies also highlight that the potential bias is likely to be more pronounced in low skilled jobs and less of a concern for high-skilled occupations and sectors (Cammeraat and Squicciarini, 2021[6]) like the one analysed in this report. That being said, not all high skilled vacancies are posted online and some are channelled through informal labour market networks (see Box 3.2)

Online vacancies may also tend to under-report certain skills as they may be "implicit" in job postings but still equally important for carrying out the tasks of the occupation at hand. This can produce an upward bias in the frequency with which certain cognitive, technical or soft skills appear relative to physical or routine skills that are less frequently mentioned.

Box 3.2. The role of informal hiring networks

The role of "informal hiring networks" can remain unaccounted for when analysing online job postings. Qualitative research done by Randstad Research Italy (forthcoming[7]) shows that these networks can be key in the case of backend programming profile (from cybersecurity to software coding). This leads to think that such roles and professions might be growing at an even faster rate than online job postings' analysis suggests in a context where demand is particularly high and job retention low. Randstad's qualitative study shows that companies looking to hire such roles need strong hiring channels, alternative to online job posting, such as educational/personal networks. In the case of start-ups for example, OJPs and HR services are utilised for the hiring of a first professional figure, usually in a senior role, who subsequently utilises their network to directly attract suitable candidates.

It is also important to notice that not all job postings collected by Lightcast contain all fields of information. Wages are, for instance, available only for a subset of vacancies.

This report and the data used therein cover 10 countries: Canada, Belgium, France, Germany, Italy, the Netherlands, Spain the United Kingdom and the United States.

Time series for Canada, Singapore, the United Kingdom and the United States is available starting from the year 2012 while information on online job postings for Belgium, France, Germany, Italy and the Netherlands starts in 2018 up to recent months of 2022. This report analyses the evolution of job postings also during the recent COVID-19 pandemic. Results, therefore, capture the significant drop in economic activity and the associated labour market disruptions starting in early 2020 when virtually all countries put in place severe measures to control the spread of the Sars-Cov-19 virus.

3.1. Using machine learning to analyse the information contained in online job postings

The information contained in online job postings is extremely rich and large. The database used in this paper spans several gigabytes of data and sums up to millions of keywords collected from job postings in different countries and over time. In addition to its size, the information contained in online job postings differs from most traditional labour market statistics (such as, for instance, labour force surveys) in that it contains information in the form of text rather than numbers and figures. Differently from standard quantitative data, text bears “semantic meaning” which can be multifaceted and ambiguous but it can also convey a far greater amount of information than just numbers and figures.

Recent advances in machine learning techniques led to the development of so-called language models which have the objective of understanding the complex relationships between words (their semantics) by deriving and interpreting the context those words appear in. Language models (and in particular Natural Language Processing- NLP- models) interpret text information by feeding it to machine learning algorithms that derive the logical rules to interpret the semantic context in which words appear. NLP and language models, used in the remainder of this paper, are therefore better suited for the analysis of text information than traditional statistics and, as such, they are used for the analysis of online job postings in the remainder of this report.

In particular, the approach taken in this report leverages “Word2Vec”, a NLP algorithm developed by researchers in Google (Mikolov et al., 2013[8]). This algorithm functions by creating a mapping between the meaning (i.e. the semantics) of words contained in text and mathematical vectors, so-called “word vectors”. Put it differently, word vectors are the mathematical representation of the meaning of the words used in online job postings. Those vectors are plotted in a high-dimensional vector space (called “graph”) where words with similar meanings occupy close spatial positions in the vector space (see Annex 3.A).

Since word vectors[3] occupy a specific place in the vector space, this makes it possible to calculate the distance (i.e. the cosine similarity) between those vectors and to rank the relationships between skills from the closest to the farthest from any given occupation. In other words, by estimating their semantic closeness, this approach allows to rank the similarities between every skill (word) vector relative to any given occupation vector.[4]

Skills that are more similar to a certain occupation are interpreted in this report as being more “relevant” to the occupation (see Annex 3.A). Using this approach is, therefore, possible to assess whether the skill “Excel” is more relevant to the occupation “Economist” or to “Painter”, based on the semantic closeness of these words’ meanings extrapolated from millions of job postings.

In the remainder of this report, the matrix of skills-to-occupations relevance scores (the Semantic Skill Bundle Matrix, SSBM) is used to identify the occupations for which digital skills are particularly relevant as well as to assess the relationship between digital skills and occupations and the speed of diffusion of the demand for digital technologies and skills across labour markets. Technical details about the machine learning approach used are provided in Annex 3.A.

It is important to notice that this report focuses on a selection of digital occupations, skills and technologies. Those have been identified by OECD experts and researchers in the Randstad Research Institute. The list of digital occupations and skills has been drafted trying to strike a balance between the need to analyse the impact of the digitalisation in various parts of the labour markets and the need to have a focused and targeted analysis of the phenomena at hand. Next chapter lists and describes the occupations and skills analysed in this report and reasoning behind their selection for the report.

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Annex 3.A. Further insights on the machine learning approach to analyse to extract skill relevance scores

Previous literature that used online vacancies to analyse labour market dynamics has, in most cases, done so via frequency-based measures and by counting the number of times certain skills would be mentioned in online job postings. Recent developments in Natural Language Processing (NLP), however, allow to leverage the information contained in online vacancies in a much more sophisticated way by looking at the semantic meaning of the textual information contained in online job postings. One such approach, the so-called word embeddings, derive a word's meaning from the context this occurs in.

These sophisticated methods leverage the distributional hypothesis, as stated by (Harris, 1954[9]), use the context in which a certain term occurs to derive the semantic meaning of the term. In their most common form, vector space models use the word's context to derive the meaning of a word and create *n*-dimensional vectors to represent that meaning. This is a so-called semantic representation which is thus encoded and distributed over all the *n* dimensions of the vector, where each dimension stands for a certain context item and its co-ordinates refer to the count of this context (Erk, 2012[10]). This quantification of the semantics of words allows to compute mathematical similarity measures that reflect the similarity between different vectors representing different words and concepts (Boleda, 2020[11]).

Intuitively word vectors are retaining the semantic meaning of words and algebraic operations can be performed using them. As word vectors retain the semantic meaning of their underlying words, the results of such mathematical operations are expected to also return semantically and logically meaningful results. For instance, once word vectors have been estimated, one could perform basic arithmetic using those vectors, such as:

$$vec(\text{“Chief”}) + vec(\text{“Male”}) + vec(\text{“Royalty”}) \approx vec(\text{“King”})$$

From a mathematical point of view, this means that if two words share an interrelated meaning (for example Chief, Male, Royalty and King) the cosine of the angle between their vector representations should be close to 1, i.e. the angle close to 0. Furthermore, negative values for the cosine refer to vector representations similar, but opposite in meaning such that vec(“King”)- vec(“Male”) ≈vec(“Queen”).

Based on these properties, one can compute measures of semantic similarity of pairs of skill keywords and occupations using paragraph vector distributed bag of words (PV-DBOW) to create the vectors representing occupations instead of simple skill keywords.[5]

Next, one can construct a Semantic Skill Bundle Matrix (SSBM) by calculating the similarity between all possible combinations of skills keywords and any given occupation pairs. Comparison of the vectors is done by looking at the so-called similarity and/ or distance between vectors. This is to say that, given two vectors representations for keyword A, and occupation B, the calculation of the similarity is done as:

$$\text{distance}(A, B) = (A \cdot B)/||A||\ ||B||$$

To illustrate the type of information contained in the SSBM, an example is given in Annex Table 3.A.1 for two randomly selected occupations “Web-Designer” and “Marketing Manager”.

Annex Table 3.A.1. Example of SSBM values for the occupation Web Designer and Marketing Manager

Web Designer (1)		Marketing Manager (2)	
Web Design	0.73	Online Marketing	0.57
Bootstrap	0.62	Marketing Management	0.52
Graphic And Visual Design	0.55	General Marketing	0.52
User Interface And User Experience	0.55	Marketing Strategy	0.50
Digital Design	0.55	Web Analytics	0.49
Javascript And Jquery	0.55	Media Strategy And Planning	0.47
Animation And Game Design	0.53	Content Development And Management	0.45
…		….	
Electrical Engineering Industry	-0.06	Civil Aviation Authority	-0.04
Occupational Hygiene	-0.06	Fuel metres	-0.04
Oil Well Intervention	-0.06	Diagnostic Technologies	-0.04
Oil Wells	-0.06	Repair	-0.06
Mechanical Products Industry Knowledge	-0.08	Thermoplastic	-0.07
Health Care Industry Knowledge	-0.11	Radio Frequency Equipment	-0.08

Note: Values reported in the table represent the cosine similarity between each skill keyword vector representation listed in column (1) and (2) and the vector representation of the occupation web designer and marketing manager. Higher values of the cosine similarity reflect higher semantic relatedness and it is interpreted as an indication of the relevance of the skill keyword for the occupation at hand.
Source: OECD calculations based on Lightcast data for the United Kingdom in 2018.

From an intuitive point of view, the closer (semantically, in meaning) a skill keyword vector representation is to the vector representation of the occupation and the more the skill is assumed to be relevant for the occupation at hand. Results in Annex Table 3.A.1 show that the skill vectors “Web Design”, “Bootstrap” and “Graphic and Visual Design” are semantically close to the occupation “Web Designer” and, hence, are interpreted in this paper as “relevant” to that occupation. Similarly, “Online Marketing”, “Marketing Management” and “General Marketing” are the most relevant skill keywords for “Marketing Managers”.

As noted by (2021[12]), intrinsic evaluation of word embeddings as the one discussed above is commonly evaluated by correlating the similarity scores with expert constructed scores. This annex provides empirical support to the hypothesis for which these SSBM scores can indeed be used to represent the relevance of skills for occupations by comparing them with the skill information contained in the O*NET database.

O*NET is a tool for career exploration and job analysis which contains detailed descriptions of more than 900 occupations and their corresponding knowledge, skills, abilities, and competencies. O*NET collects this data from job incumbents and occupation experts who assess the importance and level of each knowledge, skill, ability, and competency for each specific occupation and rank them correspondingly. Comparison between O*NET and SSBM data is useful in evaluating how well the SSBM represents the relations between occupations and skills and the cosine similarity scores represent skill relevance.

Direct comparison between SSBM scores and the O*NET values is, however, difficult to perform as the keywords in the SSBM (extracted directly from job postings) are far more granular and detailed than the categories analysed in the O*NET. For instance, in the SSBM skills such as “anaesthesiology” or “python” occur, while in the O*NET closest categories with underlying quantitative scores attached to them would be the far more aggregated knowledge areas of “Medicine and Dentistry” and “Computer and Electronics”.

Deriving a global measure for the alignment between the many SSBM dimensions and O*NET is, therefore, not a straightforward tasks. First, given the higher granularity of the keywords in the SSBM relative to O*NET, it is necessary to aggregate the data in the SSBM at the same level at that presented in O*NET.

This means, for instance, to group SSBM keywords such as Anaesthesiology, Patient care etc. into one group that can be compared with Medicine and Dentistry in O*NET.

The correlations across occupations between cosine similarity scores in the SSBM and O*NET ranked values can be used to aggregate the relevance values in the SSBM into O*NET categories. More specifically, this is done by weighting the SSBM relevance scores by the correlation of each skill keyword with every O*NET category using the values in and then taking the sum across all SSBM skills by occupation (see an example in Annex Box 3.A.1).

Annex Box 3.A.1. Mapping keywords from online job postings to O*NET categories

To describe the strategy used to carry out such grouping, let us assume, for simplicity that there are only two skills in the SSBM ("Aerospace Engineering", "Behaviour Analysis") and only two categories in O*NET, ("Education and Training" and "Engineering and Technology") one would first calculate the correlations between the SSBM and O*NET categories as follows:

Annex Table 3.A.2. Correlations between SSBM relevance scores and O*NET values

Correlations matrix between SSBM and O*NET values	Aerospace Engineering	Behavioural Analysis
Education and Training	-0.074	0.323
Engineering and Technology	0.515	-0.225

The simplified example in Annex Table 3.A.2 above indicates that occupations in the SSBM for which "Aerospace Engineering" is very relevant are also the same occupations (on average) where the knowledge of "Engineering and Technology" is also highly relevant in the O*NET (cross-occupation correlation= 0.51). On the contrary, occupations in the SSBM for which "Behavioural Analysis" is very relevant do not correlate with those for which "Engineering and Technology" in O*NET is highly relevant as one would expect.

The correlation information above can be used to aggregate the relevance values in the SSBM into O*NET categories by occupation. This is done by weighting the SSBM relevance scores by the correlation of each skill with every O*NET category using the values in Annex Table 3.A.2 and then taking the weighted sum across all SSBM skills by occupation.

In other words, consistent with the simplified example above, one can consider the occupation Engineering Technicians (SOC 17-3020) where the SBBM relevance scores for Engineering Technicians of the skills "Aerospace Engineering" and "Behaviour Analysis" are 0.570 and 0.092 respectively.

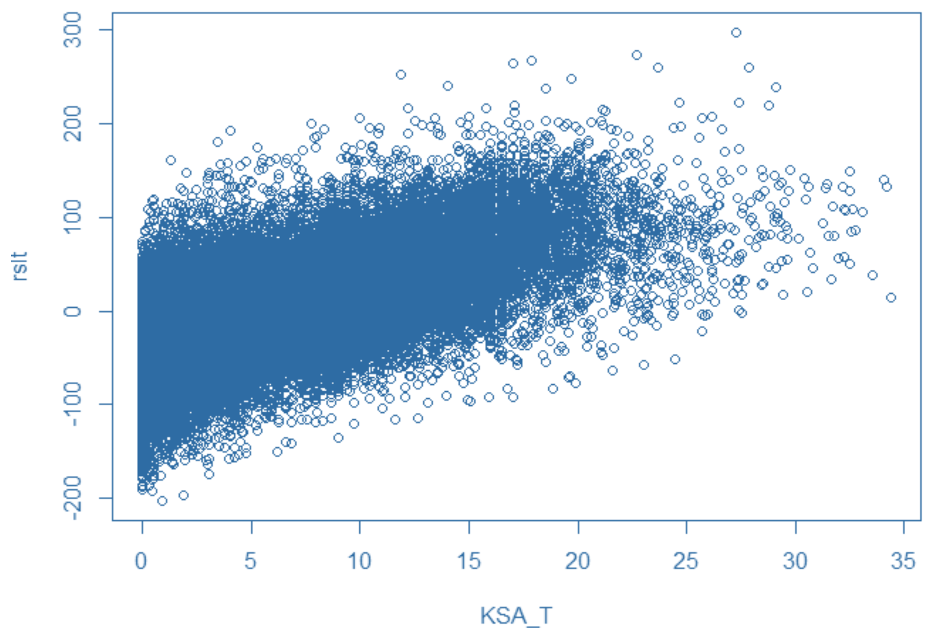
In order to translate these relevance scores into the O*NET categories of Education and Training and Engineering and Technology, one can take the sum of the SSBM relevance scores weighted by their correlation with the O*NET relevance values.

Once all skills in the SSBM have been grouped into the O*NET categories, it is possible to calculate the global correlation between SSBM (expressed in O*NET terms) and the O*NET ranked values.

In order to do so, an additional step is needed to calculate a unique measure of relevance in O*NET that combines "importance" and "level" to compare it with the relevance score in the SSBM across occupations. One can get this relevance score by multiplying the O*NET importance and level scores for each O*NET category across all occupations (OECD, 2017[3]).

Finally, this allows to correlate the O*NET values and the respective SSBM values across all combinations of occupations and skills. Annex Figure 3.A.1 shows that the correlation between the two variables is strong (0.62), positive and statistically significant providing further evidence of the alignment between the SSBM and O*NET values and of the validity of using SSBM relevance scores as an approximation of skill relevance for occupations.

Annex Figure 3.A.1. Global correlation between SSBM relevance scores and O*NET ranked values



Note: Dots represent occupations at the 6th digit US SOC level. Each dot is the combination of two values: on the horizontal axis (KSA_T) representing the O*NET scores (importance*level); on the vertical axis (rslt) the corresponding SSBM cosine similarity for every occupation.
Source: OECD calculations based on Lightcast data for the United States for the year 2019.

Notes

[1] The Anglophone countries covered in this report are: Canada, United Kingdom, United States and Singapore.

[2] The European countries covered in this report are: Belgium, France, Italy, Spain, the Netherlands

[3] One *n*-dimensional vector per skill.

[4] Occupation vectors are also calculated using a slight modification of Word2Vec called Doc2Vec (see Annex 3.A).

[5] PV-DBOW is an established technique in the natural language processing literature. A study by Mikolov et al. (2013) showed that in comparison to vector averaging (10.25%), bag-of-words (8.10%), bag-of-bigrams (7.28%) and weighted bag-of-bigrams (5.67%) the paragraph vectors, such as PV-DBOW, had the lowest error rate (3.82%). In contrast to other paragraph vector models, PV-DBOW ignores the context words in the input, but forces the model to predict words randomly sampled from the paragraph in the output. In short, each iteration of training, the model consecutively samples a text window and then a random word from this sampled text window to form a classification task for each given paragraph vector. Mikolov et al. (2013) state that in addition to being conceptually simple, PV-DBOW also requires less data to store than the distributed memory model (PV-DM).

4 The trends in labour market demands for digital professionals: Overview and dynamics across countries in online job postings

This chapter presents the analysis of recent trends in the demand for digital professionals across ten countries: Belgium, Canada, France, Germany, Italy, the Netherlands, the United Kingdom, the United States, Singapore and Spain. The results in this chapter are based on the analysis of millions of job postings collected from the internet and disaggregated at the occupation level. Results compare the dynamics across countries, showing the significant increase in the demand for digital professionals over time but also the negative effect that the COVID-19 crisis has had on labour markets and on the growth in the demand of some digital professions.

Digital occupations are diverse and range from jobs involving routine tasks, such as web maintenance, to more complex tasks like software development. The universe of digital occupation is large and constantly expanding with new jobs.

This chapter focuses on a selection of digital occupations to investigate the trends in the demand for digital professionals across a varied range of countries. The digital occupations analysed in this chapter have been selected for their importance in the digital transition but also with an eye to cover a broad and diverse spectrum of roles that have been affected by digitalisation in various sectors. The selection of occupations was undertaken by the OECD in collaboration with Randstad Research Italy,[1] who offered valuable feedback in the identification of the digital professions analysed herein (see Box 4.1).

Box 4.1. The selection of occupations across countries

The number of selected occupations covered in this chapter varies depending on data availability in each country. For Canada, the United Kingdom and the United States, 20 occupations have been selected, while for Singapore 17 occupations have been identified.[1] In the case of EU countries (Belgium, France, Germany, Italy, the Netherlands and Spain), 14 countries were finally selected. The final selection for all countries is shown in Figure 4.1.[2]

The precise number of selected occupations in Anglophone countries (Canada, Singapore, the United Kingdom and the United States) and in the EU (Belgium, France, Germany, Italy, the Netherlands and Spain) varies due to the way online job postings (OJPs) are classified into occupational taxonomies in the two groups of countries. As discussed in Chapter 3, the classification of occupations is made on the basis of the proprietary Lightcast occupational taxonomy for Anglophone countries (Canada, United Kingdom and the United States) and of ISCO for EU countries (Belgium, France, Germany, Italy, the Netherlands and Spain).

The advantage of using the Lightcast taxonomy lies in its high level of occupational granularity, where jobs are categorised at the eight-digit level. In contrast, the ISCO taxonomy used for EU countries is only available at the fourth digit. This means that the occupational categorisation for Anglophone countries is more detailed, covering more specific occupations than in the case of the EU. On the other hand, this also entails that when analysing online job postings through the ISCO taxonomy a larger share of postings is gauged than when mapping OJPs to more disaggregated (and smaller in size) occupations using Lightcast taxonomy. The fact that two different taxonomies are used to categorise occupations for Anglophone and EU countries also calls for some caution when comparing results between the two sets of geographical areas, given that overlap between the two occupational taxonomies is only partial. As much as possible, this chapter will try to draw references between the two sets of data to ensure the widest comparability.

1. In particular, in contrast for the rest of Anglophone countries analysed, for Singapore online job postings data is missing for the following occupations: computer scientist, data scientist, and data engineer.
2. The selection of occupations for Anglophone and EU countries, respectively, has been made in a way that the two groups of countries and occupations can be compared despite occupations being classified using different taxonomies. In particular, the ISCO-SOC crosswalk has been used with the aim of ensuring that comparisons between the two sets of data are meaningful. However, as noted throughout this chapter, some caution should still be exercised when making comparisons given the differing level of disaggregation in the occupational categorisation.

4.1. Selecting and comparing occupations across countries

Figure 4.1 presents the digital occupations under examination in this chapter. To ease comparison and in order to simplify visualisation across countries, these are grouped into four broad categories:

1. Computer and data analysts / administrators,
2. Software developers, programmers and engineers,
3. ICT technicians and data entry clerks, and
4. ICT and HR managers / marketing specialists

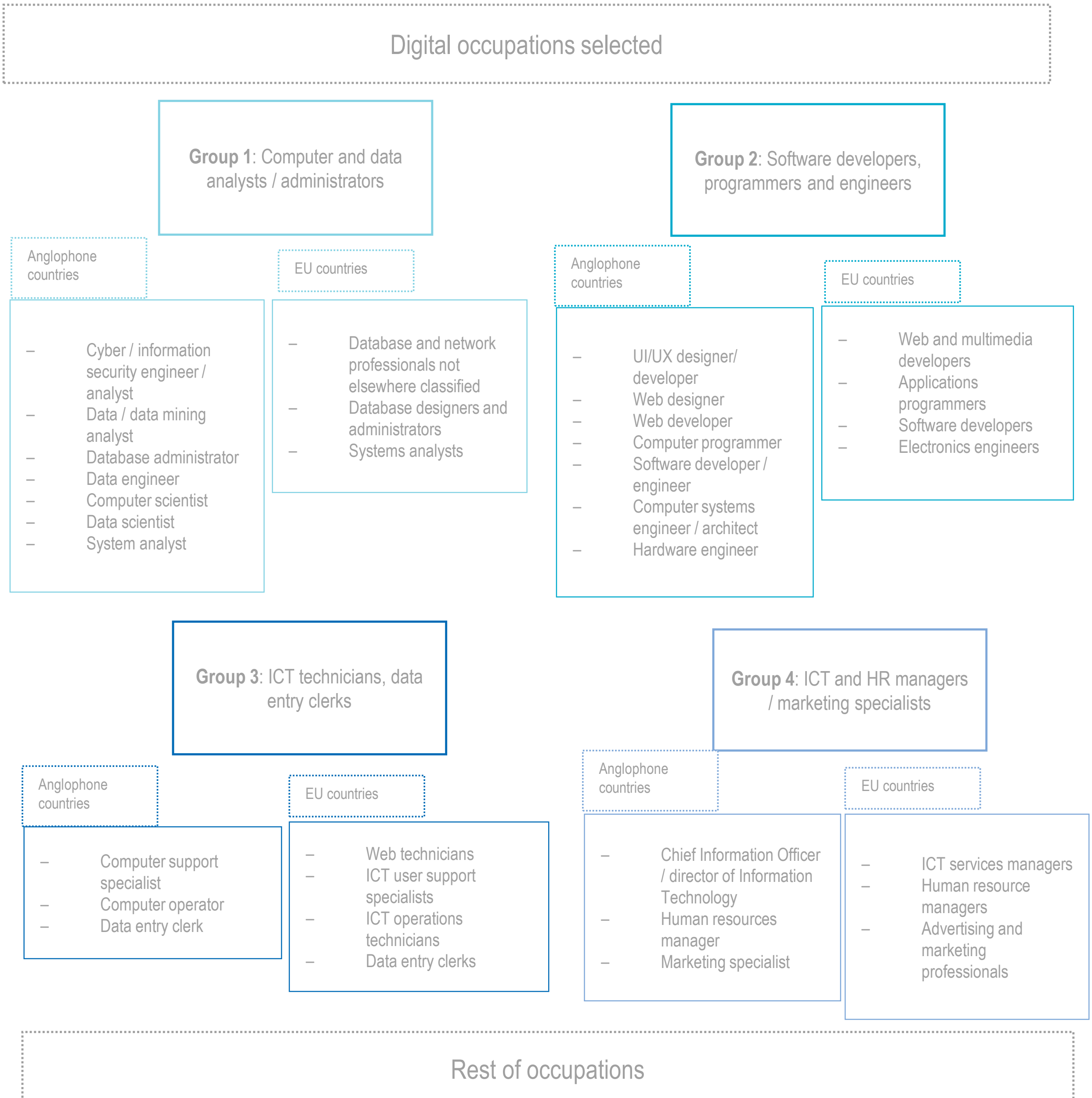
The group of computer and data analysts / administrators, includes occupations such as system analysts or database administrators. System analysts “conduct research, analyse and evaluate client information technology requirements, procedures or problems, and develop and implement proposals, recommendations, and plans to improve current or future information systems” (ILO, 2016[1]). Database designers and administrators, instead, “design, develop, control, maintain and support the optimal performance and security of databases” (ILO, 2016[1]).

The group of software developers, programmers, and engineers comprises occupations such as UI/UX designers/developers[2] who “develop and implement websites, web applications, application databases, and interactive web interfaces. [They also] Evaluate code to ensure that it is properly structured, meets industry standards, and is compatible with browsers and devices. Optimize website performance, scalability, and server-side code and processes (…)” (US Bureau of Labour Statistics, 2010[2]). Another example is the case of software developers, who “research, analyse and evaluate requirements for existing or new software applications and operating systems, and design, develop, test and maintain software solutions to meet these requirements” (ILO, 2016[1]).

The third group comprises ICT technicians and data entry clerks. Occupations in this group typically require lower skills than in the rest of groups.[3] Data entry clerks “enter coded, statistical, financial and other numerical data into electronic equipment, computerized databases, spreadsheets or other data repositories using a keyboard, mouse, or optical scanner, speech recognition software or other data entry tools. They enter data into mechanical and electronic devices to perform mathematical calculations” (ILO, 2016[1]). Other occupations in this group are computer operators[4] and ICT operations technicians.[5] Those latter, for instance, are technicians that “support the day-to-day processing, operation and monitoring of information and communications technology systems, peripherals, hardware, software and related computer equipment to ensure optimal performance and identify any problems” (ILO, 2016[1]).

The fourth and last group examined in this chapter pools together ICT and HR managers / marketing specialists. This group includes occupations such as ICT service managers, who “plan, direct and co-ordinate the acquisition, development, maintenance and use of computer and telecommunication systems, either as the manager of a department or as the general manager of an enterprise or organisation that does not have a hierarchy of managers”.

Figure 4.1. Categorisation of selected digital occupations

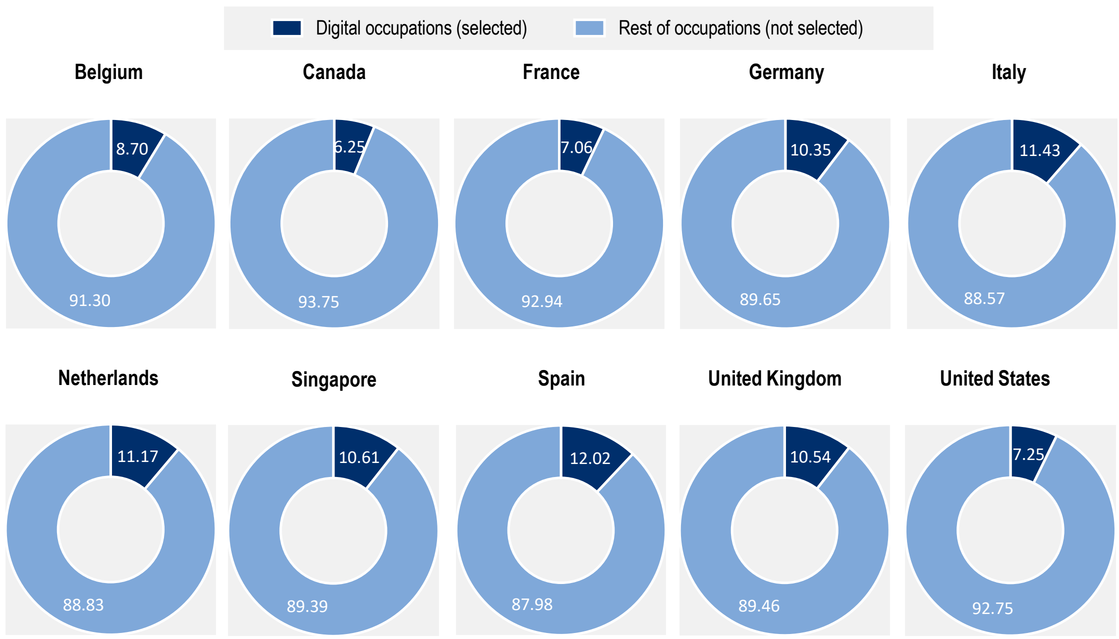


Note: Online job postings on Data Engineer, Data Scientist and Computer Scientist for Singapore is unavailable.
Source: OECD.

The digital occupations identified in this chapter represent a significant share of the labour market demand that appears online. On average, the selected digital occupations represent over 6% of total OJPs in Canada, more than 7% in the US, and close to 11% in the United Kingdom and Singapore (Figure 4.2).[6] In EU countries, the digital occupations selected for the analysis range from 7% of the total OJPs in France to 9% in Belgium, 10% in Germany, 11% in the Netherlands, and close to 12% in Italy and Spain.[7]

Figure 4.2. Selected digital occupations as a share of total job postings

Share of total postings (%), average for all years



Note: The shares are calculated as the average share over the selected time period: 2012-18 for Anglophone countries, and 2018-21 for EU countries except for Italy, where data exists as of 2014.
Source: OECD calculations based on Lightcast data.

Going deeper in the disaggregation of the results, Figure 4.3 presents the relative prevalence of each of the four broad occupational categories out of the total OJPs selected in this report (Figure 4.1 provided more detail on this classification).

Out of the selected digital occupations, software developers, programmers and engineers are the most prevalent across OJPs in countries. In the United Kingdom, for instance, approximately to 2 in every 3 online job postings for digital professionals (within the selected digital occupations for this study) are seeking software developers and programmers. In the United States the share of OJPs for software developers and engineers is 56% of the total postings related to digital professionals while in Spain, Canada and Singapore those shares are close to 50% of the total OJPs for digital jobs.

In Germany and France, the share of OJPS for software developers and programmers are slightly lower than in above mentioned countries, but still considerable (37% and 36%, respectively).

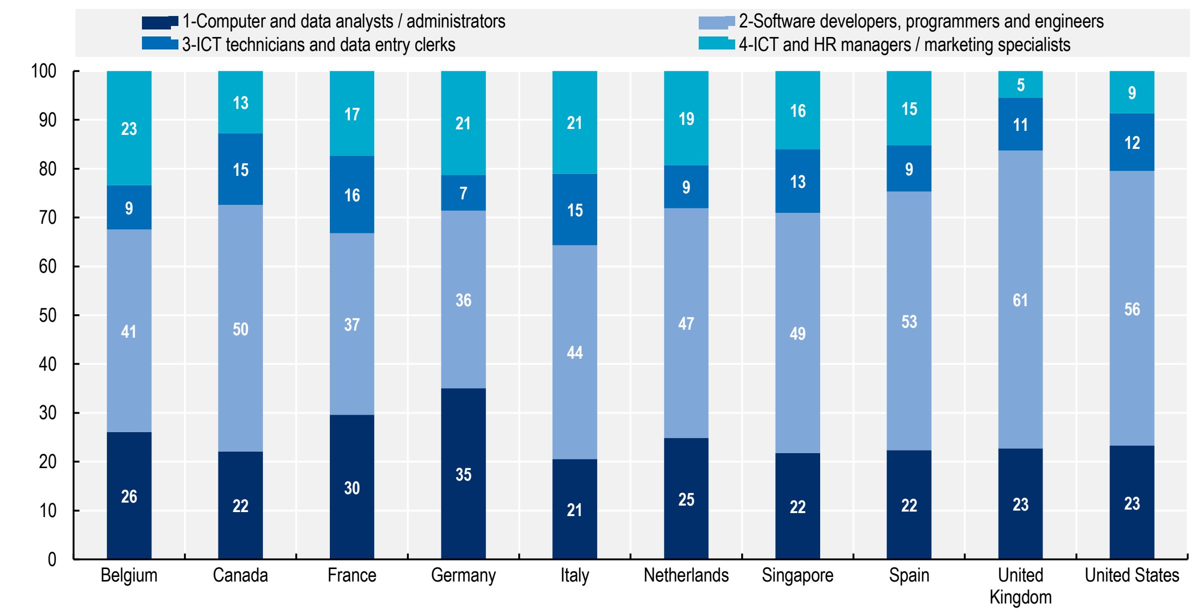
Computer and data analysts/administrators are also relatively numerous across OJPs, representing over 1 in every 5 of the selected digital occupations.[8]

ICT technicians and data entry clerks, instead, represent a smaller fraction of overall OJPs in all countries. In fact, these are below 20% for all analysed countries, ranging from 7% in Germany or 9% in Belgium, the Netherlands and Spain to around 15-16% in Canada, Italy and France.

Finally, ICT and HR managers / marketing specialists show the lowest prevalence over the total OJPs for the selected occupations in the United Kingdom (5%), whereas they are much more prominent in Belgium (23%) or in Germany and Italy (21%). This group includes ICT services managers, human resource managers and advertising and marketing professionals.[9]

Figure 4.3. Breakdown of selected digital occupations by broad occupational groups

Share of each category of job postings by occupation over selected digital occupations



Note: The shares are calculated as the average share over the selected time period: 2012-18 for Anglophone countries, and 2018-21 for EU countries except for Italy, where data exists as of 2014.
Source: OECD calculations based on Lightcast data.

4.2. Trends in online job postings for digital professionals across countries

This section describes the evolution of the OJPs for the selected digital occupations over time. Figure 4.4 shows the increase/decrease in the publication of job postings online for each occupations and since the first year for which data is available by using the volumes of OJPs in the initial year as a benchmark (i.e. as an index with value 100).

Generally, results in this section show the significant increase in the volume of online job postings published for most digital occupations but also the important negative impact that the COVID-19 crisis has had across most labour markets and, as a consequence, on some digital professions.

Focusing on the occupations where demand has increased, results below show that postings for data engineers and data scientists in Canada, the United Kingdom and the United States experienced a striking growth in the past few years. Conversely, data for Belgium, Germany or the Netherlands show a more mixed scenario, where the demand for some digital occupations has been heavily impacted during the pandemic years and has not yet fully recovered as of the end of 2021. In the case of EU countries, it is important to notice that OJPs time series only start in 2018 (with the exception of Italy in 2014) and that virtually all digital occupations in EU countries had been trending significantly upwards in pre-pandemic years. As the COVID-19 crisis struck, this implied a heavy correction in the demand for most occupations that has not yet been fully reabsorbed at the time of writing this report.

4.2.1. Computer and data analysts' trends

In a world that is reliant on interconnected devices and where large amounts of sensitive data are collected, stored and used to improve decision making, cyber threats and data breaches pose significant risks for governments and businesses. In order to reduce vulnerability to cyberattacks, organisations are increasingly investing in cybersecurity and IT risk management. This is reflected in the results looking at the evolution of the demand for cybersecurity professionals.

In the United States, Canada and Singapore, the online job postings for cyber / information security engineers / architects have, in fact, trended up steadily. The number of postings in this category has been steadily growing since 2012 and only declined in 2020, in coincidence with the COVID-19 crisis. In 2021, the demand for cybersecurity professionals has started increasing again and volumes of OJPs are back at their highest values (176 000 new online postings for cyber / information security engineers / architects in the United States). A similar trend can be observed in the United Kingdom where OJPs for cyber / information security engineers / architects in the United Kingdom are in 2021 nearly four times higher than in 2012 (from 10 600 to nearly 40 000).

OJPs for data mining analysts have also increased strikingly in all countries for which information is available and, especially, in Singapore (from slightly above 300 posting-s in 2012 to nearly 12 000 in 2021). Likewise, growth in the United States for data mining analysts has been significant with the only exception of the year 2020 (at the beginning of the pandemic) while the volume of postings in 2021 is at its record levels of 94 000 per year.

These results suggest that, as the Digital Revolution has certainly triggered an increasing availability of data and that professionals such as data mining analysts have also become increasingly important for businesses as their skills (analysing large data sets to identify patterns, trends, using statistical techniques and programming software) are becoming of paramount importance for employers to manage production and plan strategically all types of activities from marketing to logistics and distribution.

In EU countries, the availability of OJPs information starts in 2018 (with the exception of Italy, where data starts in 2014). Hence, pre-pandemic information is only available for the years 2018 and 2019, while afterwards statistics on OJPs have been heavily affected – as expected – by the strong declines in economic activity experienced by all economic sectors. That being said, even during the pandemic period, some digital occupations have experienced increased demand relative to the pre-pandemic period.

For instance, in Italy and France, job postings for database and network professionals have increased steadily since the start of the available time series. In Italy, in particular, the number of OJPs increased nearly 9 times between 2014 and 2021, although it is worth noting that the initial postings were relatively few (nearly 240). In France, online vacancies for database and network professionals more than doubled in 2021 (relative to 2018).

Conversely, for Belgium, Germany, the Netherlands and Spain, online postings for those professionals reached their peak in 2019 to then decline as the COVID-19 crisis hit. As of now, the levels of OJPs for those professionals have not yet recovered significantly but in the longer run, an increase in the demand is expected in most of those occupations. This trend is also observed for online vacancies for system analysts and database designers and administrators, where postings increased in the pre-crisis period between 2018 and 2019, but then declined coinciding with the advent of the COVID-19 crisis.

4.2.2. Software developers, programmers and engineers' trends

In the universe of digital occupations, software developers, programmers and engineers have experienced some of the most notable growth rates. In Canada, for instance, the number of job postings published online for UI / UX designers / developers in 2021 was more than three time larger than in 2012 (growing from 760 to 2 500 postings). Similarly, in the United Kingdom, online postings for UI / UX designers / developers in 2021 reached their maximum peak of close to 15 000. In the United States, the growth in online vacancies for UI / UX designers / developers was very significant, especially between 2017 and 2019, a period of sustained growth that was only interrupted in 2020 with the COVID-19 crisis. However, in 2021, as in other countries, the number of postings for UI / UX designers / developers started mounting again and are now close to the highest figure per year that was reached before the pandemic in 2019, with a total of 70 800 postings.

Some of these trends can be observed also in EU countries. In Belgium, for instance, online vacancies for web and multimedia developers doubled between 2018 and 2019 (increasing from around 4 100 to 7 700) but fell considerably during 2020 and, even more so, in 2021 during the pandemic years. More broadly, with the exception of France, postings for software developers and programmers and electronic engineers in the analysed EU countries are still far from the peak levels recorded in 2019. In the Netherlands and Italy, for instance, OJPs for electronics engineers, software developers, web and multimedia developers and applications programmers showed a sharp increase in 2019 to then decline in 2020 and 2021 with signs of a slight recovery in 2021 in the Dutch case.

4.2.3. ICT technicians and data entry clerks' trends

Among digital occupations, ICT technicians provide support for the deployment and maintenance of computer infrastructure and web technology. They also contribute to the diagnosis and resolution of technical problems.

While some of the tasks of these jobs may be more routine-intensive than those of other digital occupations, they are still essentials for ICT infrastructures to work properly. Similarly, as countries and firms transit towards a fully digital environment, the work of data entry clerks may be particularly important in sectors that are still in the process of digitalising, despite a potentially negative labour market outlook in the future due to the low skilled nature of these jobs.[10]

As a confirmation of the key role of some of these professionals during the years of the digital transformation, the analysis of online job postings for data entry clerks shows that the demand for them has increased significantly in the United States (from 25 000 in 2012 to almost 68 000 in 2021). In Canada, OJPs for data entry clerks have also followed, overall, an increasing trend since 2012 to then decrease with the advent of the pandemic in 2020 and recover to roughly pre-pandemic levels in 2021. In the United Kingdom, instead, vacancies for data entry clerks peaked in 2017 before declining yearly up until 2020. However, in 2021, postings more than doubled relative to the initial year of the pandemic showing that there is still demand for workers supporting the digitalisation of analogic processes as in the case of data entry clerks.

Similar trends are observed in some EU countries such as Belgium and the Netherlands. In Belgium, for instance, OJPs for data entry clerks have been consistently above the 2018 level and peaked in 2020. In the Netherlands, postings for data entry clerks increased annually since 2018, with the exception of 2020, and are in 2021 at their highest level (around 1 400).

In other EU countries, however, the COVID-19 crisis seems to have had a stronger negative impact on these jobs with OJPs following an inverted-U pattern: a strong growth before the pandemic and a correction during the years of the crisis. For example, in Spain and Germany, postings for data entry clerks increased in between 2018 and 2019, while they experienced a strong decline during 2020 and have not recovered the pre-crisis levels in 2021. In Germany, for instance, a peak of 7 200 OJPs was reached in 2019, and the 2021 levels are at 4 400.

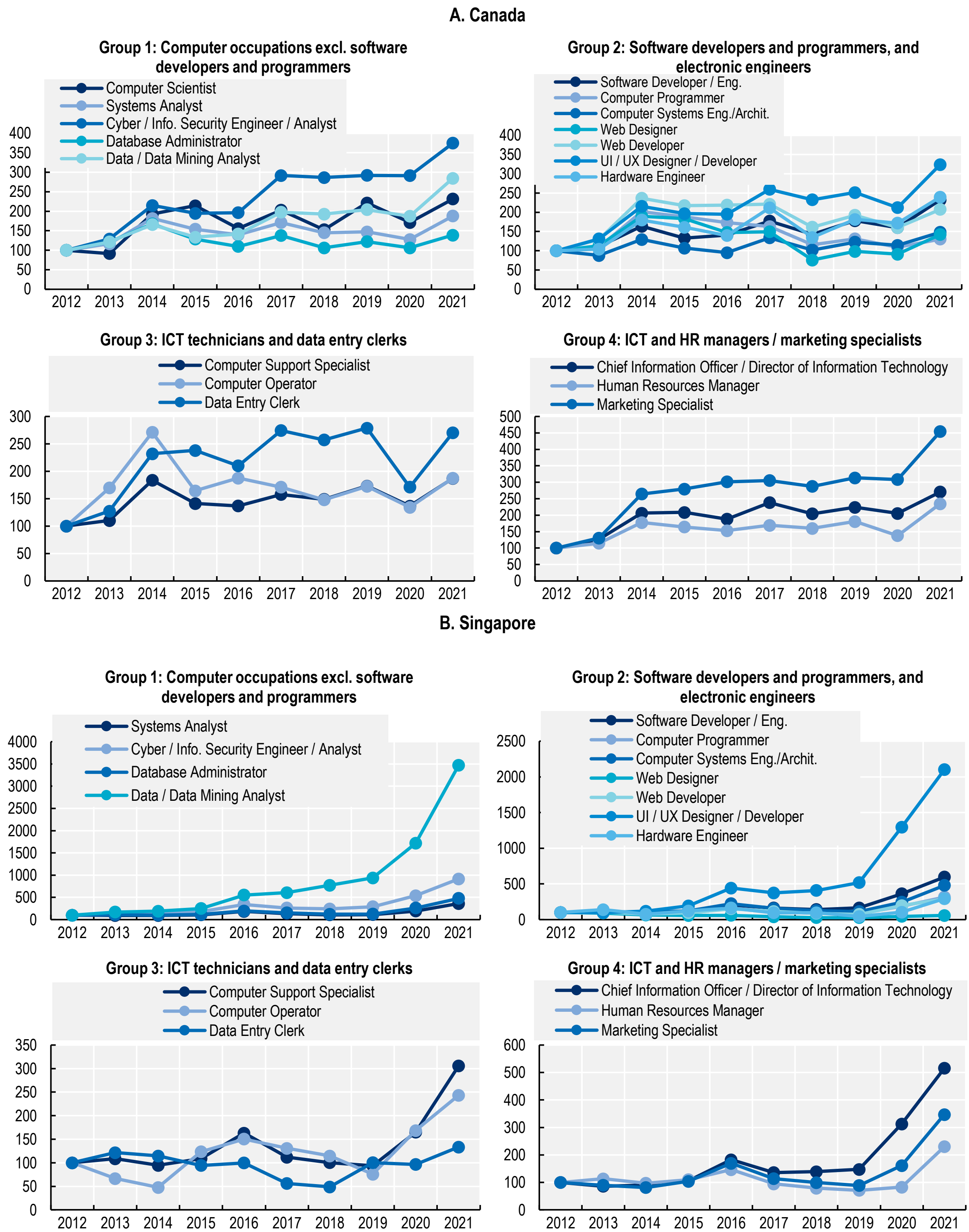
4.2.4. ICT and HR managers/ marketing specialists' trends

Vacancies for high-skilled digital professionals, such as Chief Information Officers / directors of IT, human resources managers, and marketing specialists have increased significantly in the four Anglophone countries under study. For Canada, this is particularly the case for marketing specialists, whose number of job postings has increase more than 4 times since 2012, from around 1900 to 8 600 in 2021. For the United Kingdom and the United States, postings for marketing specialists exhibit a strong growth, though the pattern has been rather volatile across years. In the United States, for instance, postings for marketing specialists declined during the pandemic in 2020 (when postings amounted to less than 65 000) before increasing very strongly to reach over 126 000 postings in 2021. For the United Kingdom, vacancies for marketing specialists declined since 2017, but the levels in 2021 picked up again significantly (8 600 postings). In Singapore, job postings related to Chief Information Officer / director of IT have also quadrupled compared to 2012 levels, although it is worth noting that the starting levels were below 200.

In the European countries analysed, online vacancies for these high-skilled occupations have followed relatively similar dynamics across countries, peaking in 2019 and, afterwards, declining in 2021, possibly due to the strong impact of the pandemic on economic activity. In 2019, the growth for OJPs concerning ICT service managers was particularly high in Italy, where the volume of OJPs in 2019 (3 100) was more than five times that of 2014 (640). Since then, however, postings have declined during the years of the pandemic and are yet to recover. In Germany, new postings for ICT services managers have instead declined since 2018, moving from around well above 21 000 postings in 2018 to around 15 200 in 2021.

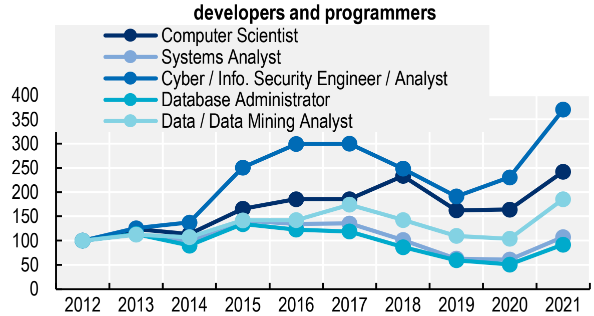
Figure 4.4. Evolution of digital job postings by country

Index (initial year's level = 100)

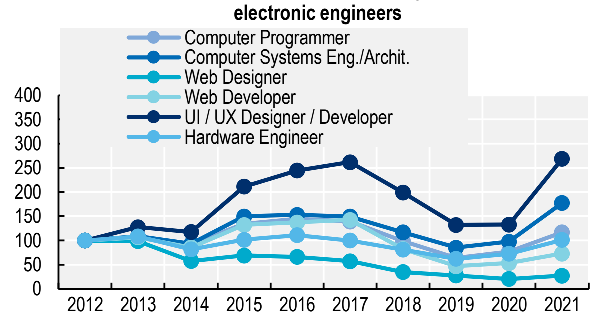


C. United Kingdom

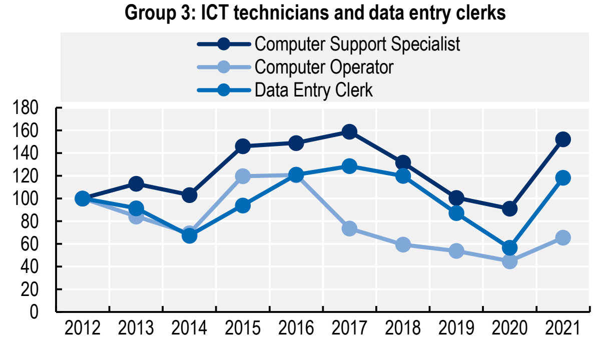
Group 1: Computer occupations excl. software developers and programmers



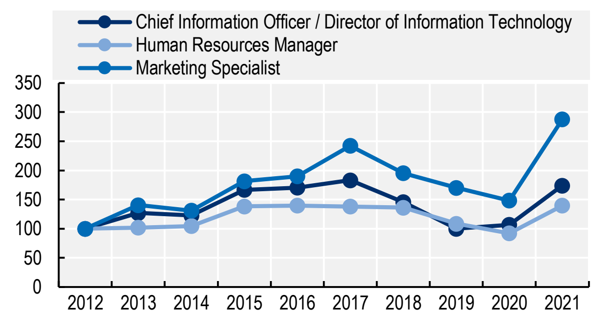
Group 2: Software developers and programmers, and electronic engineers



Group 3: ICT technicians and data entry clerks

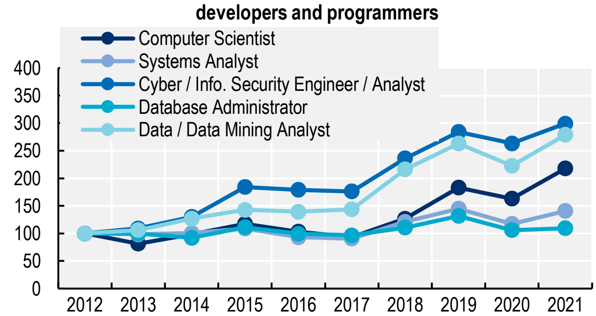


Group 4: ICT and HR managers / marketing specialists

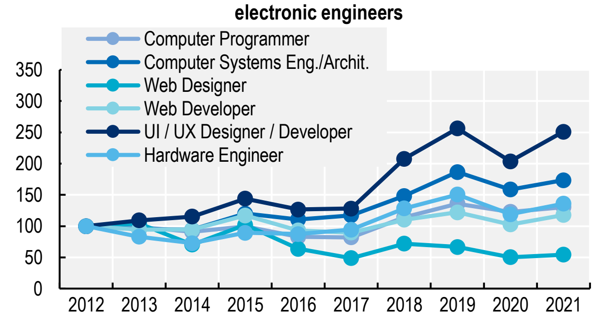


D. United States

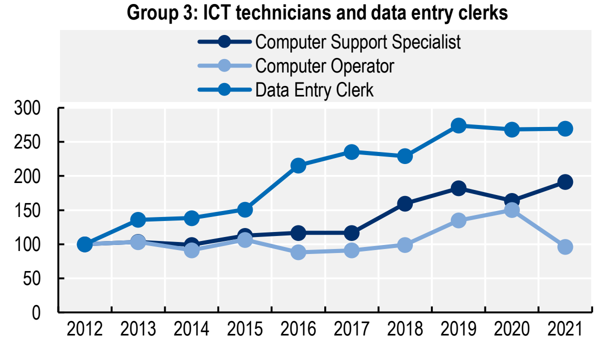
Group 1: Computer occupations excl. software developers and programmers



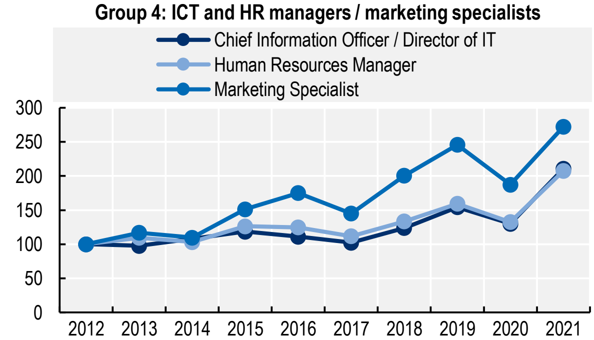
Group 2: Software developers and programmers, and electronic engineers



Group 3: ICT technicians and data entry clerks

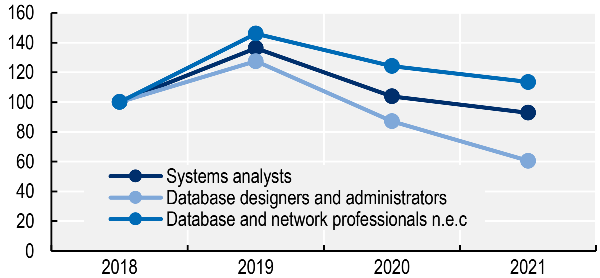


Group 4: ICT and HR managers / marketing specialists

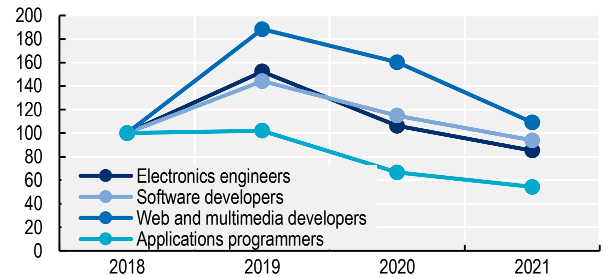


E. Belgium

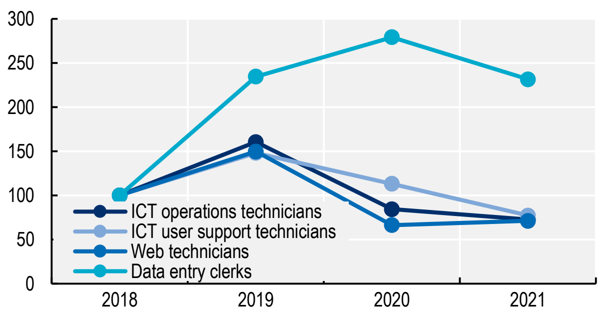
Group 1: Computer occupations excl. software developers and programmers



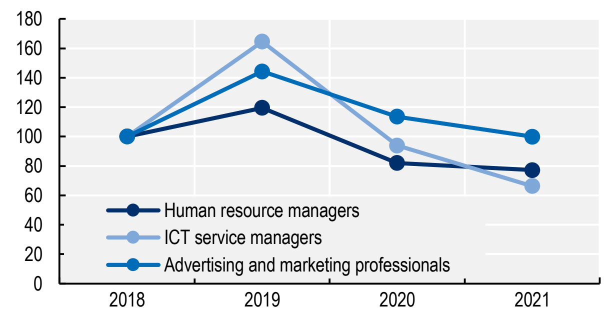
Group 2: Software developers and programmers, and electronic engineers



Group 3: ICT technicians and data entry clerks

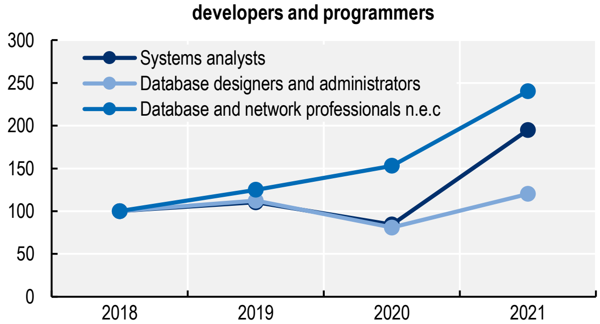


Group 4: ICT and HR managers / marketing specialists

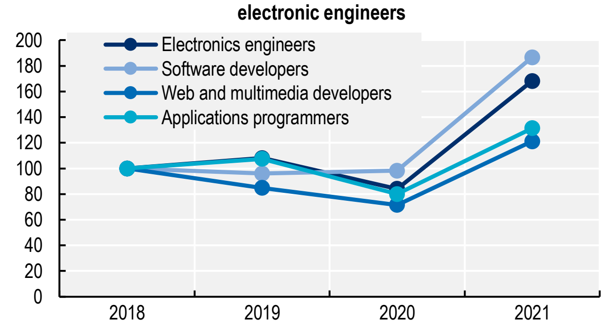


F. France

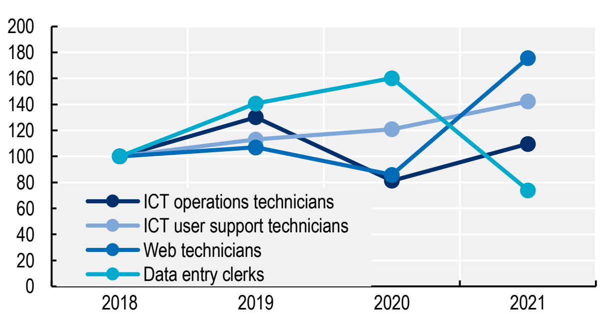
Group 1: Computer occupations excl. software developers and programmers



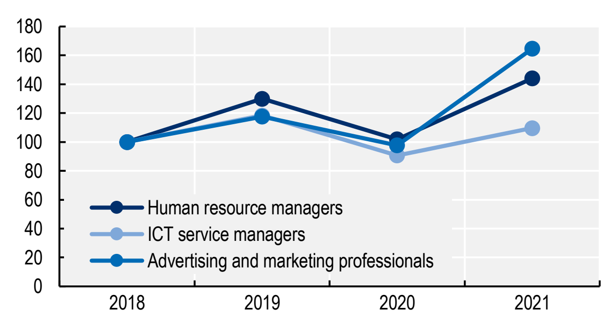
Group 2: Software developers and programmers, and electronic engineers



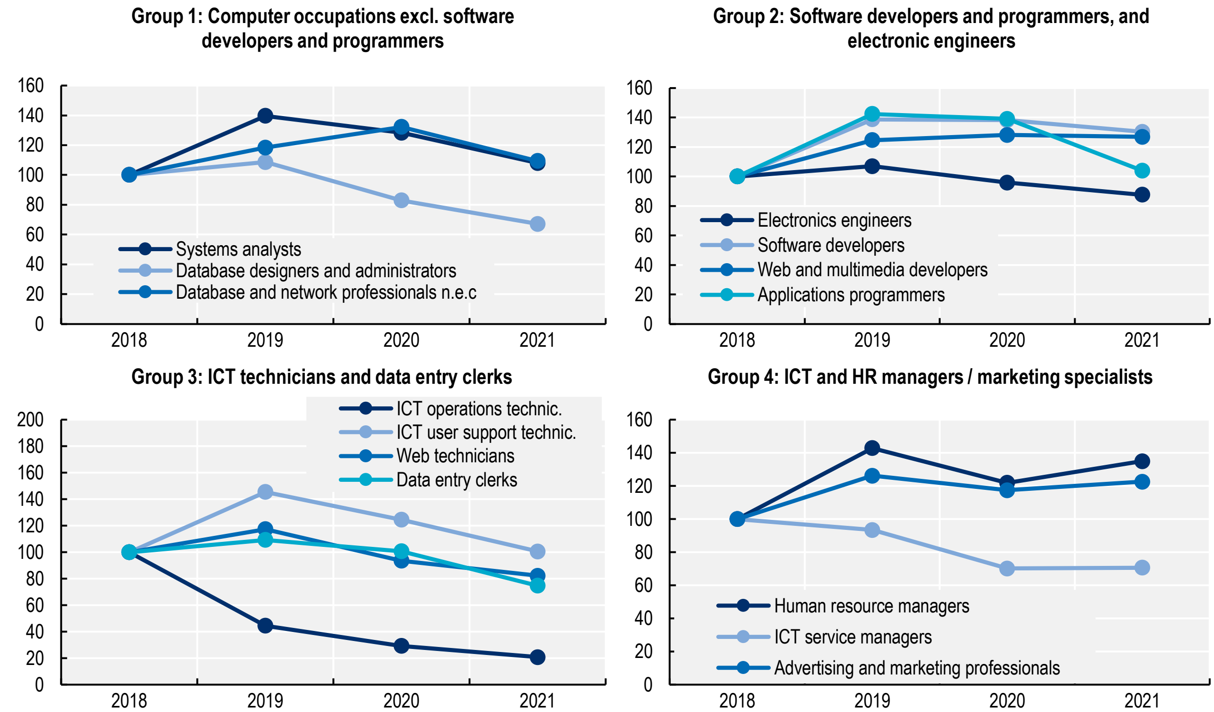
Group 3: ICT technicians and data entry clerks



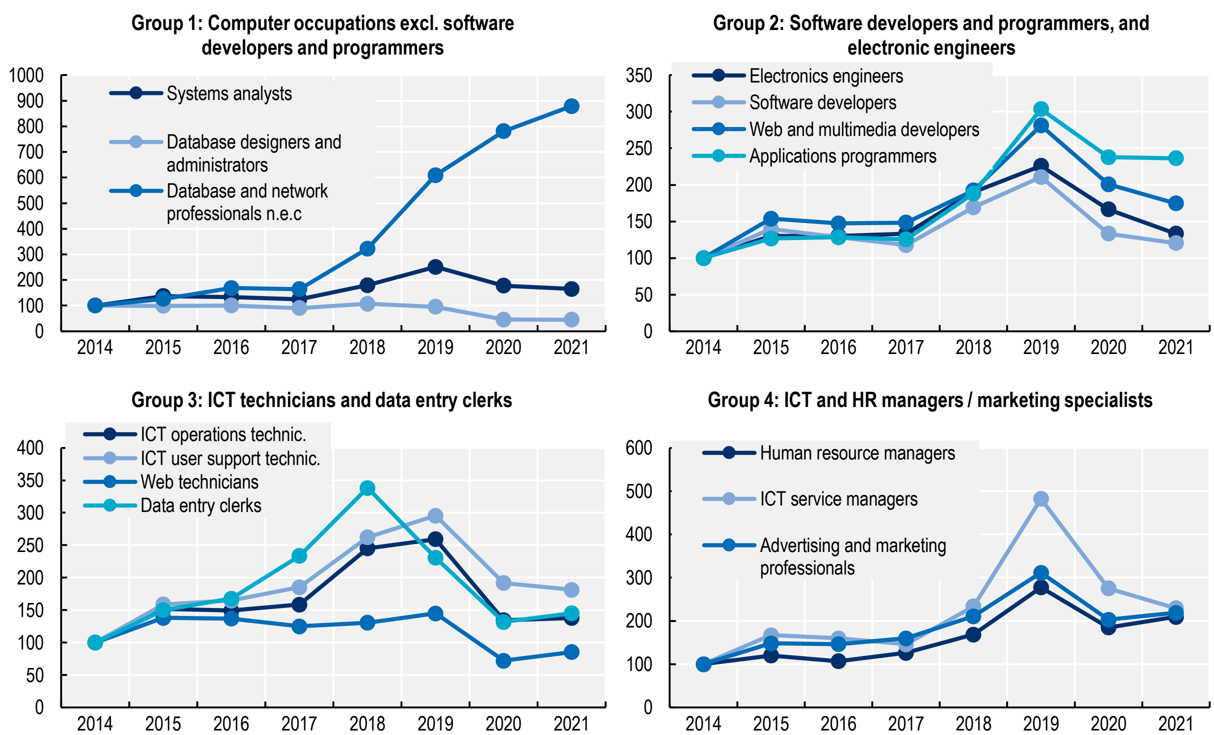
Group 4: ICT and HR managers / marketing specialists



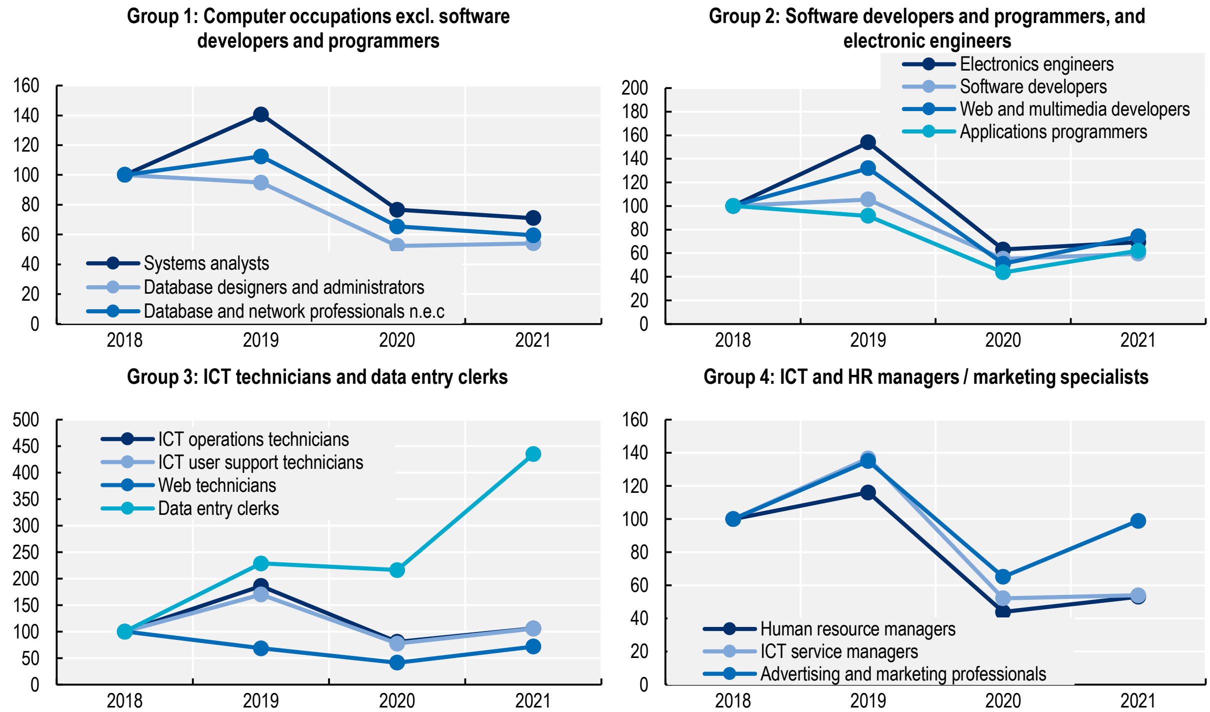
G. Germany



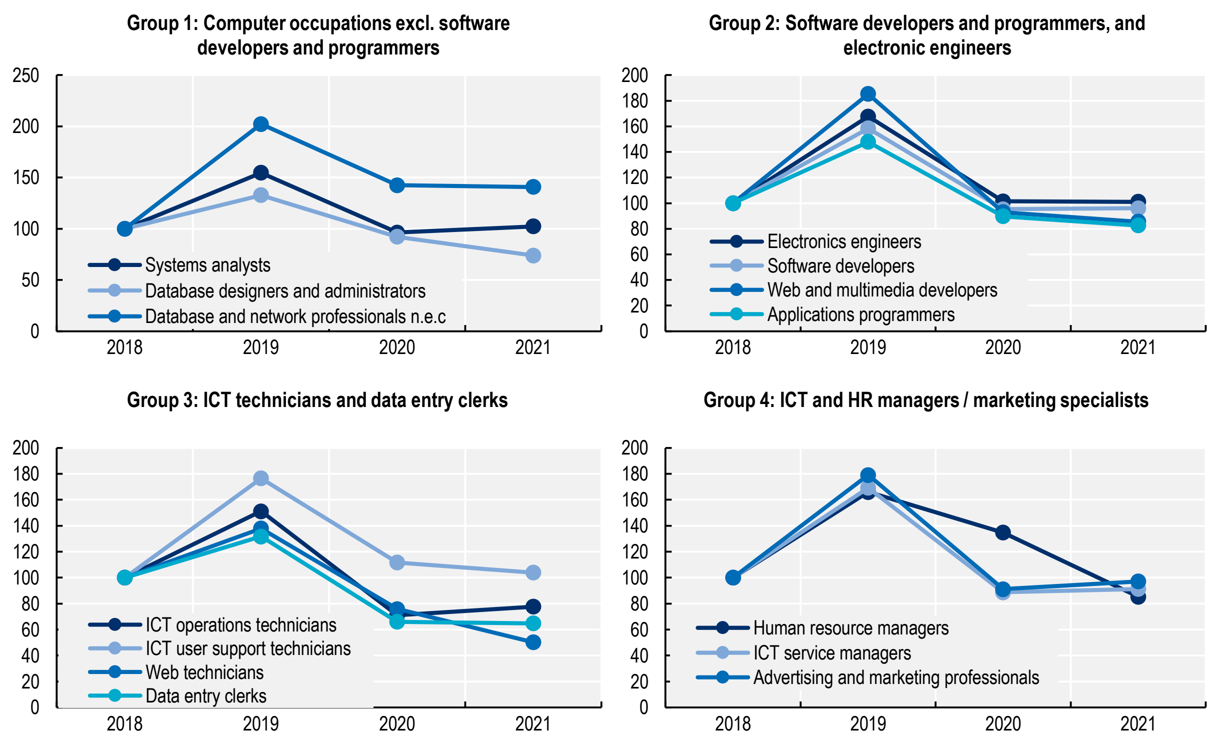
H. Italy



I. Netherlands



J. Spain



Source: OECD calculations based on Lightcast data.

4.3. In focus: The demand for digital professionals in the United States

In addition to the occupations that have been analysed above for the full cross-section of countries in this report, this section examines and identifies trends in a wider range of digital occupations by taking the United States as a case study, a country that is usually considered at the forefront of technological innovation and adoption. This section is useful as the growth in some of the occupations analysed herein has been very significant and these dynamics are, therefore, worth to be highlighted separately.

Results in this section are presented for occupations belonging to the occupational group of “computer and mathematical occupations (SOC-15) and for the years preceding the COVID-19 pandemic in order to show the magnitude of those longer-run dynamics when unaffected by the unprecedented shock in pandemic years.

4.3.1. Occupations in high demand in the United States

As this section is mostly concerned with medium to long term trends, Table 4.1 presents the top digital occupations (in SOC-15) ranked by the growth in the number of online job postings in between 2012 and 2019 excluding, therefore, the downturn during the years affected by the COVID-19 pandemic.

Table 4.1. Digital occupations in high demand in the United States

	Number of online postings in 2019	Growth between 2012 and 2019 (%)
Data scientist	42 340	3 260%
Data engineer	36 888	2 320%
Search engine operations specialist	16 000	238%
Business intelligence architect/ developer	67 000	178%
Mobile applications developer	41 000	126%
Database architect	52 000	111%
Technology consultants	37 000	111%
Data warehousing specialist	33 000	108%

Source: OECD calculations based on Lightcast data.

Results show that data scientists and data engineers have been experiencing a significative growth in the volume of new vacancies published online, signalling the increase in their demand in the US labour market. OJPs for data scientists increased, for instance, by more than 40 times going from merely 1 260 postings in 2012 to over 50 000 in 2021. A similar extraordinary growth is also registered for OJPs for data engineers which went from roughly 1 500 in 2012 to close to over 47 000 in 2021.[11]

The growing importance and relevance of these occupations lies in the central role they play in the collection and analysis of data used in a variety of different sectors that are nowadays relying on interconnected devices and where large flows of data are used to reduce mistakes in production, oversee different stages of production and minimise costs by automatising processes. Data scientists, for instance, are “employed to analyse and interpret complex digital data, such as the usage statistics of a website, especially in order to assist a business in its decision-making” (Oxford Languages, n.d.[3]) while data engineers, “administer, test, and implement computer databases, applying knowledge of database management systems. Co-ordinate changes to computer databases. May plan, co-ordinate, and implement security measures to safeguard computer databases” (US Bureau of Labour Statistics, 2010[2]).

While the figures for data scientists and data engineers are certainly striking, it is important to read them with some caution as the volumes of job postings in the initial year may be an underestimation of the true labour market demand as online job portals (from which the presented information comes from) were still relatively new “market places” and some demand may have been channelled through more traditional advertisements. The sharp increases in the demand for these professionals in recent years, however, is warranted and the information coming from OJPs clearly identifies a booming trend that has been reshaping the IT and digital sector.

Table 4.1 and Figure 4.5 also show that other occupations have been growing very rapidly with significant increases in the volume of job postings published online. The demand for business intelligence architects / developers, for instance, has been increasing rapidly since 2012. Similar to data engineers, business intelligence architects / developers are key to businesses, as they leverage software and services to transform data into actionable insights that can inform an organisation's strategic and tactical business decisions. Postings for this occupation have almost tripled[12] by 2021 relative to 2012, as businesses have become increasingly aware of the need to use their data effectively for business planning and strategical decisions.

In a context where businesses are increasingly using data for decision-making and optimisation of processes, postings for database architects have also followed a similar trend, having nearly doubled in relation to their initial levels. The tasks of database architects vary, including the design of strategies for the use and structure of enterprise databases, multidimensional networks and warehouse systems, as well as modelling, designing and constructing large databases or optimising models for infrastructure and workflow.

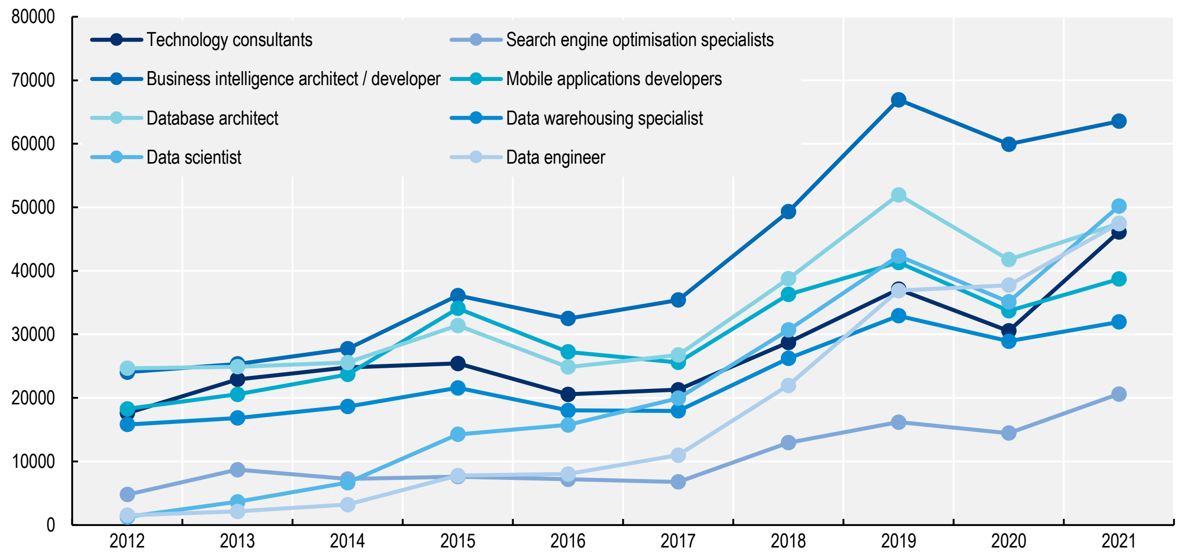
Mobile applications developers – who are in charge to create, programme, test and maintain apps and mobile platforms – are also in very high demand. Table 4.1 shows that online job postings for this occupation have more than doubled in the last nine years and this trend may continue in the future as mobile applications are becoming a standard mean to deliver services in virtually all sectors of economic activity, from entertainment to banking, education and retail.

Among the fastest growing digital occupations, the role of technology consultants (sometimes referred to as innovation or technology brokers) has also been on the rise. As the digital transition is requiring firms to transform digitally and new roles such as those of technology consultants are emerging, helping businesses to restructure their activities. Technology Consultant work with clients to help them transform the way they use technology where "traditionally, these transformations have been geared towards improving business processes, reducing costs, maximising use of tech opportunities, and more. Today, they encompass (…) more – from digital strategy to technology change projects" (PwC, n.d.[4]). Results from online job postings (Figure 4.5) indicate that vacancies for technology consultants have been on a significant rise, with over 46 000 postings in 2021, almost three times larger than the levels of 2012.

Online job postings for data warehousing specialists have also more than doubled in the last few years, increasing from 16 000 in 2012 to almost 32 000 in 2021. Some of their tasks include the development of processes and procedures for data management within an organisation, or creating software applications for data storage and management. Given the growing storage of data, their task is crucial in making procedures more efficient.

Interestingly, online job postings for search engine optimisation (SEO) specialists have also increased substantially since 2012, from 4 800 to close to 21 000 in 2021. SEO specialists analyse a client's website and carries out any changes that may be needed for its optimisation in search engines. Their role is paramount in the current environment where business positioning has gained momentum.

Figure 4.5. Evolution of number of OJPs for growing digital occupations in the United States



Source: OECD calculations based on Lightcast data.

4.3.2. Occupations showing a stable (or decreasing) demand in the United States

Along with the digital occupations that have been booming in recent years, the demand for other roles within the digital economy has instead remained relatively stable, or even declined. It is hence worth analysing also those roles as stable or declining trends may reveal longer-run dynamics.

Table 4.2 lists the growth of this smaller set of occupations within SOC group of "computer and mathematical occupations" between 2012 and 2019 while Figure 4.6 shows the detailed evolution year-by-year. Among digital occupations, webmaster/ administrators are the only ones showing a mild decline in the volume of job postings relative to the initial year (-17%) though, in recent years, the demand for them has started picking up again. Other occupations, and in particular telecommunications engineering specialists have also seen only modest increases in the volume of new job postings over time, possibly pointing to a weakening demand for those professionals.

Table 4.2. Digital occupations with stable or decreasing demand in the United States

	Number of online postings in 2019	Growth between 2012 and 2019 (%)
Computer programmer	83 981	36%
Network / systems administrator	128 464	24%
Telecommunications engineering specialist	16 030	16%
Webmaster / administrator	6 100	-17%

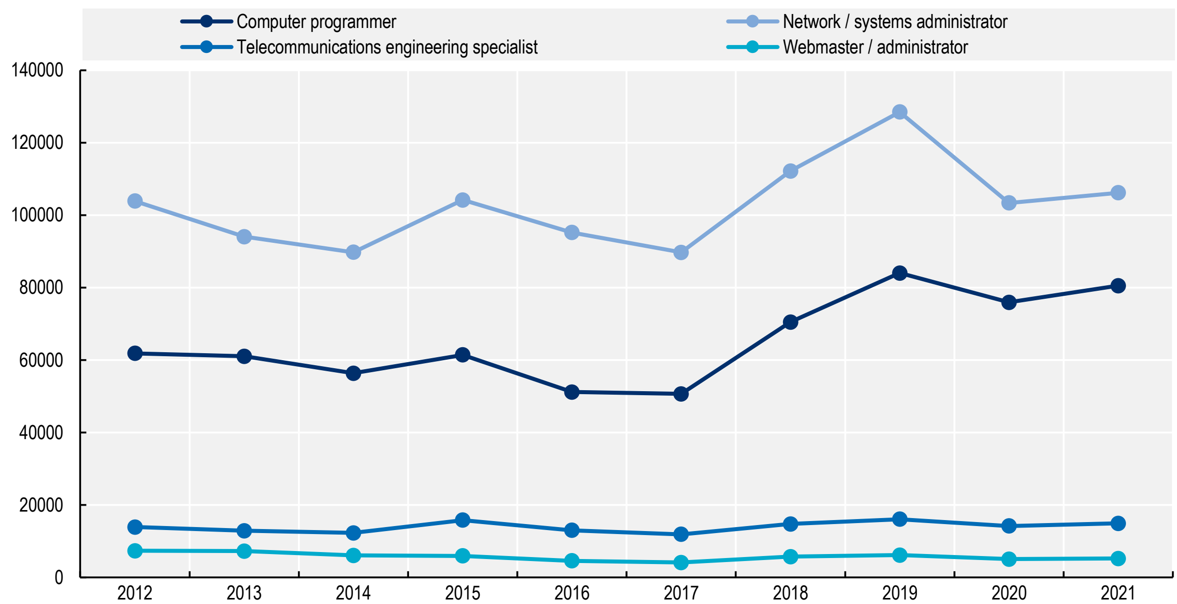
Source: OECD calculations based on Lightcast data.

Network administrators are in charge of keeping the organisation's network up to date and operating as intended. Systems administrators undertake similar tasks, but they work more directly with computer software (e.g. installation, maintenance or data recovery). The analysis of OJPs for network / systems administrators shows a rather volatile pattern between 2012 and 2017. After 2017 and up until 2019, postings instead increased steadily, before being negatively hit in 2020 with the advent of the pandemic. In 2021, postings show some signs of recovery, with levels being slightly higher than those registered in 2020. This limited growth is also highlighted in the Occupational Outlook Handbook, developed in 2022 by the US Bureau of Labour

Statistics (2022[5]), who project postings related to this occupation to grow 5% in 2020-30, slower than the average for all occupations.

Finally, online vacancies for computer programmers, after having declined between 2012 and 2017, have started to increase significantly pointing to potential labour market bottlenecks in the near future if such demand is not met by workers with adequate skills to fill the new positions.

Figure 4.6. Evolution of OJPs for stable digital occupations in the United States



Source: OECD calculations based on Lightcast data.

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Annex 4.A. Detailed results at the occupation level

Annex Table 4.A.1. Canada: Number of online job postings per year

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Computer and data analysts / administrators										
Computer Scientist	70	64	135	150	109	142	107	155	120	162
Data Scientist	7	33	117	193	350	449	649	949	972	1 348
Systems Analyst	4 979	5 795	9 044	7 674	6 940	8 513	7 209	7 328	6 348	9 353
Cyber / Info. Security Eng. / Analyst	1 352	1 743	2 907	2 635	2 657	3 945	3 876	3 948	3 940	5 070
Database Administrator	2 338	2 837	3 920	3 003	2 568	3 218	2 478	2 856	2 483	3 240
Data Engineer	14	22	33	40	118	225	284	614	682	1 018
Data / Data Mining Analyst	1 153	1 400	1 910	1 540	1 634	2 281	2 222	2 353	2 158	3 281
Software developers, programmers and engineers										
Software Developer / Eng.	15 612	17 363	25 548	20 745	22 014	27 647	22 231	27 822	24 998	36 238
Computer Programmer	2 544	2 777	5 130	4 788	4 406	4 146	2 946	3 335	2 776	3 315
Computer Systems Eng. / Architect	2 371	2 076	3 063	2 533	2 249	3 168	2 415	2 905	2 703	3 512
Web Designer	373	422	707	685	550	557	283	366	339	530
Web Developer	2 540	3 281	6 012	5 525	5 559	5 615	4 099	4 887	4 074	5 269
UI / UX Designer / Developer	759	995	1 634	1 492	1 480	1 971	1 766	1 908	1 609	2 459
Hardware Engineer	167	174	300	269	233	353	225	303	287	400
ICT technicians and data entry clerks										
Computer Support Specialist	5 746	6 333	10 554	8 117	7 862	9 059	8 562	9 953	7 853	10 756
Computer Operator	73	124	198	120	137	125	108	126	98	137
Data Entry Clerk	1 050	1 337	2 437	2 500	2 205	2 881	2 700	2 926	1 798	2 840
ICT and HR managers / marketing specialists										
Chief Information Officer / Director of IT	514	651	1 060	1 072	966	1 225	1 050	1 152	1 056	1 391
Marketing Specialist	2 021	2 319	3 591	3 321	3 095	3 420	3 234	3 652	2 788	4 746

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Human Resources Manager	1 895	2 476	5 010	5 299	5 714	5 787	5 451	5 941	5 847	8 606
Rest of occupations	441 673	681 568	1 202 809	1 103 723	1 060 807	1 163 610	1 147 788	1 380 325	1 223 192	1 691 123
TOTAL	487 251	733 790	1 286 119	1 175 424	1 131 653	1 248 337	1 219 683	1 463 804	1 296 121	1 794 794

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.2. Singapore: Number of online job postings per year

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Computer and data analysts / administrators										
Computer Scientist	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a
Data Scientist	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a
Systems Analyst	3 818	3 510	3 571	4 112	7 087	5 200	4 120	4 299	7 402	13 755
Cyber / Info. Security Eng. / Analyst	1 024	1 154	1 446	1 865	3 484	2 669	2 471	2 959	5 500	9 378
Database Administrator	1 737	1980	1 788	2006	3 427	2 642	2 118	2 143	4 531	8 288
Data Engineer	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a
Data / Data Mining Analyst	341	578	653	857	1 882	2066	2 631	3 201	5 850	11 834
Software developers, programmers and engineers										
Software Developer / Eng.	9 965	10 084	9 340	11 746	20 266	16 279	14 167	16 383	36 069	59 536
Computer Programmer	1 883	1 818	1 616	1 743	3 053	2090	1 679	1 603	3 554	5 933
Computer Systems Eng. / Architect	4 125	4 562	4 283	5 126	9 224	6 494	5 257	4 689	10 124	19 816
Web Designer	721	669	473	418	437	285	204	195	331	420
Web Developer	1 417	1 475	1 076	1 349	2 168	1 624	1 258	1 053	2 788	4 129
UI / UX Designer / Developer	178	173	211	344	786	668	726	924	2 306	3 740
Hardware Engineer	160	223	122	194	260	154	155	70	167	471
ICT technicians and data entry clerks										
Computer Support Specialist	5 734	6 224	5 431	6 239	9 346	6 414	5 749	5 378	9 460	17 543
Computer Operator	111	74	53	137	167	145	127	84	187	270
Data Entry Clerk	1 061	1 290	1 215	1 001	1 059	594	519	1 063	1 023	1 414
ICT and HR managers / marketing specialists										
Chief Information Officer / Director of IT	173	149	156	184	316	235	241	255	541	892
Marketing Specialist	5 257	5 955	5 114	5 777	7 690	4 983	4 146	3 735	4 348	12 090
Human Resources Manager	3 502	3 134	2 847	3 644	5 936	3 974	3 478	3 112	5 650	12 144
Rest of occupations	466 980	478 605	457 484	492 719	691 917	460 421	392 856	408 708	630 878	1 289 393
TOTAL	508 187	521 657	496 879	539 461	768 505	516 937	441 902	459 854	730 709	1 471 046

Note: For Singapore, online postings for computer scientists, data scientists and data engineers is unavailable.
Source: OECD calculations based on Lightcast data.

Annex Table 4.A.3. United Kingdom: Number of online job postings per year

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Computer and data analysts / administrators										
Computer Scientist	1 037	1 284	1 179	1 720	1926	1924	2 420	1 686	1 702	2 514
Data Scientist	179	768	1 276	3 993	5 798	11 116	8 699	6 687	7 049	10 986
Systems Analyst	37 022	41 809	35 909	52 269	49 619	50 129	37 422	23 222	22 573	39 824
Cyber / Info. Security Eng. / Analyst	10 615	13 350	14 587	26 615	31 776	31 846	26 393	20 288	24 488	39 298
Database Administrator	33 591	38 144	30 191	45 083	41 197	39 935	29 053	19 957	17 046	30 821
Data Engineer	956	1 407	1 441	2 522	3 857	6 115	6 188	5 521	8 760	20 238
Data / Data Mining Analyst	56 434	63 456	60 523	80 078	80 373	98 233	80 523	61 905	58 517	104 795
Software developers, programmers and engineers										
Software Developer / Eng.	238 650	265 742	225 010	362 409	379 556	427 734	297 448	191 617	231 024	380 864
Computer Programmer	27 394	29 645	25 475	36 876	39 730	38 170	26 935	17 576	21 112	31 999
Computer Systems Eng. / Architect	39 436	42 854	36 683	59 127	60 401	58 958	46 151	33 662	38 488	69 957
Web Designer	7 966	7 862	4 583	5 484	5 258	4 555	2 763	2 211	1 632	2 178
Web Developer	98 150	104 610	84 100	129 608	134 983	139 880	80 974	45 879	52 377	71 700
UI / UX Designer / Developer	5 574	7 121	6 550	11 787	13 630	14 594	11 085	7 361	7 406	14 969
Hardware Engineer	4 364	4 724	3 568	4 432	4 839	4 356	3 543	2 707	3 171	4 411
ICT technicians and data entry clerks										
Computer Support Specialist	66 724	75 392	68 781	97 450	99 393	105 950	87 811	67 125	60 734	101 641
Computer Operator	310	261	215	371	374	228	184	167	139	203
Data Entry Clerk	4 434	4 055	2 983	4 165	5 368	5 700	5 319	3 866	2 511	5 243
ICT and HR managers / marketing specialists										
Chief Information Officer / Director of IT	12 152	15 455	14 922	20 253	20 723	22 277	17 704	12 153	12 984	21 150
Marketing Specialist	20 238	20 608	21 198	28 029	28 299	27 939	27 573	22 011	18 674	28 292
Human Resources Manager	1 227	1 724	1 610	2 227	2 330	2 975	2 397	2089	1 822	3 529
Rest of occupations	5 033 724	6 004 014	5 450 037	6 798 134	7 630 494	8 280 361	7 897 370	6 397 915	5 834 325	8 967 339
TOTAL	5 700 177	6 744 285	6 090 821	7 772 632	8 639 924	9 372 975	8 697 955	6 945 605	6 426 534	9 951 951

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.4. United States: Number of online job postings per year

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Computer and data analysts / administrators										
Computer Scientist	4 519	3 679	4 444	5 314	4 665	4 226	5 732	8 273	7 369	9 844
Data Scientist	1 260	3 649	6 644	14 272	15 749	19 936	30 696	42 340	35 123	50 175
Systems Analyst	119 301	117 430	119 985	129 972	111 126	108 029	144 642	172 809	140 069	167 979
Cyber / Info. Security Eng. / Analyst	58 911	64 262	76 568	108 520	105 548	103 794	139 203	167 385	155 028	176 352
Database Administrator	89 629	89 426	82 557	99 783	89 102	86 519	99 196	118 055	95 018	98 032
Data Engineer	1 524	2 137	3 204	7 766	8 019	10 983	21 973	36 888	37 729	47 434
Data / Data Mining Analyst	33 587	35 595	42 654	47 974	46 821	48 228	72 609	88 304	74 827	93 714
Software developers, programmers and engineers										
Software Developer / Eng.	549 292	509 986	495 853	632 326	564 180	592 382	820 633	1 061 418	900 090	1 020 960
Computer Programmer	61 812	61 034	56 354	61 415	51 130	50 652	70 470	83 981	75 912	80 519
Computer Systems Eng. / Architect	100 702	95 709	94 884	120 768	111 560	118 008	149 323	187 859	159 677	174 556
Web Designer	12 832	13 364	9 032	13 059	8 172	6 259	9 233	8 536	6 467	6 983
Web Developer	101 336	95 889	95 644	118 606	94 251	90 865	111 788	123 604	104 056	119 402
UI / UX Designer / Developer	28 207	30 805	32 474	40 607	35 727	36 133	58 565	72 300	57 397	70 799
Hardware Engineer	8 658	7 189	6 284	7 725	7 552	8 169	11 120	13 036	10 299	11 774
ICT technicians and data entry clerks										
Computer Support Specialist	128 767	133 355	127 478	144 758	150 305	150 215	205 638	234 241	210 914	246 179
Computer Operator	3 417	3 526	3 115	3 639	3 015	3 113	3 390	4 607	5 131	3 291
Data Entry Clerk	25 127	34 132	34 770	37 870	54 172	59 135	57 583	68 808	67 350	67 690
ICT and HR managers / marketing specialists										
Chief Information Officer / Director of IT	18 308	17 890	19 750	21 681	20 331	18 722	22 664	28 257	23 804	38 555
Marketing Specialist	48 751	53 405	50 306	61 566	60 844	54 535	65 095	77 735	64 679	101 165
Human Resources Manager	46 381	54 216	50 883	70 210	81 233	67 325	92 998	113 997	86 897	126 218
Rest of occupations	12 818 523	16 873 610	17 827 737	19 284 447	22 087 074	20 833 750	26 909 522	32 774 677	34 152 816	42 478 505
TOTAL	14 260 844	18 300 288	19 240 620	21 032 278	23 710 576	22 470 978	29 102 073	35 487 110	36 470 652	45 190 126

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.5. Belgium: Number of online job postings per year

	2018	2019	2020	2021
Computer and data analysts / administrators				
Systems analysts	14 299	19 489	14 845	13 274
Database designers and administrators	631	804	550	382
Database and network professionals n.e.c.	1 606	2 345	1995	1 823
Software developers, programmers and engineers				
Electronics engineers	2 473	3 767	2 627	2 106
Software developers	16 720	24 098	19 202	15 702
Web and multimedia developers	4 086	7 695	6 549	4 461
Applications programmers	1 567	1 599	1 043	852
ICT technicians and data entry clerks				
ICT operations technicians	899	1 442	759	653
ICT user support technicians	3 603	5 337	4 078	2 782
Web technicians	243	364	161	173
Data entry clerks	539	1 265	1 506	1 248
ICT and HR managers / marketing specialists				
Human resource managers	1 842	2 203	1 510	1 423
ICT service managers	2 899	4 772	2 723	1924
Advertising and marketing professionals	9 883	14 270	11 227	9 878
Rest of occupations	680 019	883 188	756 054	579 973
TOTAL	741 309	972 638	824 829	636 654

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.6. France: Number of online job postings per year

	2018	2019	2020	2021
Computer and data analysts / administrators				
Systems analysts	55 013	60 691	46 423	107 258
Database designers and administrators	1 892	2 122	1 530	2 274
Database and network professionals n.e.c.	1 229	1 537	1 880	2 954
Software developers, programmers and engineers				
Electronics engineers	7 076	7 644	5 947	11 896
Software developers	55 902	53 683	54 885	104 344
Web and multimedia developers	12 092	10 248	8 650	14 646
Applications programmers	2 480	2 666	1984	3 258
ICT technicians and data entry clerks				
ICT operations technicians	4 450	5 790	3 619	4 877
ICT user support technicians	16 921	19 132	20 463	24 071
Web technicians	3 140	3 358	2 696	5 515
Data entry clerks	7 935	11 168	12 710	5 864

	2018	2019	2020	2021
ICT and HR managers / marketing specialists				
Human resource managers	5 347	6 947	5 442	7 703
ICT service managers	13 018	15 404	11 806	14 267
Advertising and marketing professionals	18 168	21 367	17 742	29 905
Rest of occupations	2 645 523	3 208 988	3 340 048	3 465 205
TOTAL	2 850 186	3 430 745	3 535 825	3 804 037

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.7. Germany: Number of online job postings per year

	2018	2019	2020	2021
Computer and data analysts / administrators				
Systems analysts	214 633	299 599	275 429	231 676
Database designers and administrators	8 566	9 302	7 099	5 750
Database and network professionals n.e.c.	11 506	13 621	15 209	12 579
Software developers, programmers and engineers				
Electronics engineers	14 980	16 028	14 364	13 126
Software developers	167 909	232 996	232 144	218 826
Web and multimedia developers	27 220	33 924	34 890	34 548
Applications programmers	22 125	31 508	30 784	23 019
ICT technicians and data entry clerks				
ICT operations technicians	12 264	5 451	3 573	2 539
ICT user support technicians	33 817	49 195	42 099	34 013
Web technicians	5 397	6 335	5 048	4 434
Data entry clerks	7 181	7 842	7 231	5 361
ICT and HR managers / marketing specialists				
Human resource managers	13 991	19 991	17 059	18 881
ICT service managers	21 457	20 040	15 055	15 164
Advertising and marketing professionals	113 445	143 224	133 237	139 057
Rest of occupations	5 573 289	7 491 100	7 864 914	6 396 169
TOTAL	6 247 780	8 380 156	8 698 135	7 155 142

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.8. Italy: Number of online job postings per year

	2014	2015	2016	2017	2018	2019	2020	2021
Computer and data analysts / administrators								
Systems analysts	7 153	9 814	9 546	8 912	12 856	17 948	12 691	11 796
Database designers and administrators	683	674	684	616	729	651	310	305
Database and network professionals n.e.c.	236	297	397	388	761	1 438	1 843	2075
Software developers, programmers and engineers								
Electronics engineers	1 625	2 115	2 117	2 163	3 088	3 673	2 707	2 167
Software developers	14 964	20 873	19 250	17 597	25 323	31 531	19 954	18 017
Web and multimedia developers	1 630	2 505	2 400	2 419	3 137	4 582	3 271	2 846
Applications programmers	644	815	826	809	1 213	1955	1 531	1 522
ICT technicians and data entry clerks								
ICT operations technicians	1 091	1 658	1 628	1 728	2 675	2 828	1 467	1 505
ICT user support technicians	2 635	4 185	4 345	4 879	6 908	7 784	5 051	4 777
Web technicians	1 094	1 510	1 498	1 368	1 427	1 585	788	934
Data entry clerks	527	790	884	1 231	1 783	1 215	694	765
ICT and HR managers / marketing specialists								
Human resource managers	498	597	533	628	839	1 382	921	1 043
ICT service managers	643	1 073	1 027	939	1 502	3 101	1 770	1 475
Advertising and marketing professionals	5 823	8 625	8 522	9 312	12 271	18 133	11 815	12 735
Rest of occupations	270 501	371 428	386 089	446 769	641 101	694 197	508 364	559 181
TOTAL	309 747	426 959	439 746	499 758	715 613	792 003	573 177	621 143

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.9. The Netherlands: Number of online job postings per year

	2018	2019	2020	2021
Computer and data analysts / administrators				
Systems analysts	12 261	17 233	9 398	8 715
Database designers and administrators	793	752	416	429
Database and network professionals n.e.c.	2 189	2 461	1 433	1 302
Software developers, programmers and engineers				
Electronics engineers	1 697	2 613	1 071	1 177
Software developers	19 208	20 267	10 611	11 427
Web and multimedia developers	9 868	13 032	5 039	7 324
Applications programmers	1 792	1 642	783	1 112
ICT technicians and data entry clerks				
ICT operations technicians	368	685	297	390
ICT user support technicians	3 345	5 693	2 585	3 541
Web technicians	152	104	63	109
Data entry clerks	319	730	690	1 388

	2018	2019	2020	2021
ICT and HR managers / marketing specialists				
Human resource managers	759	881	333	403
ICT service managers	2 372	3 242	1 237	1 280
Advertising and marketing professionals	8 498	11 478	5 536	8 405
Rest of occupations	352 544	643 912	352 164	487 938
TOTAL	416 165	724 725	391 656	534 940

Source: OECD calculations based on Lightcast data.

Annex Table 4.A.10. Spain: Number of online job postings per year

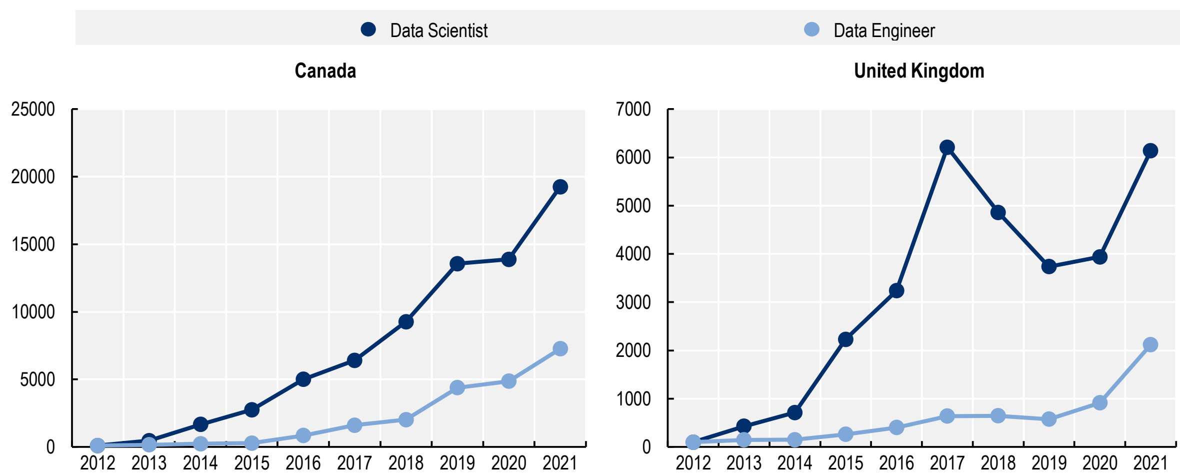
	2018	2019	2020	2021
Computer and data analysts / administrators				
Systems analysts	20 659	31 945	19 904	21 124
Database designers and administrators	1 807	2 400	1 665	1 333
Database and network professionals n.e.c.	1 607	3 249	2 290	2 262
Software developers, programmers and engineers				
Electronics engineers	1 675	2 808	1 698	1 693
Software developers	47 569	75 392	45 301	45 649
Web and multimedia developers	6 644	12 306	6 177	5 686
Applications programmers	2 184	3 230	1959	1 804
ICT technicians and data entry clerks				
ICT operations technicians	426	644	303	331
ICT user support technicians	8 633	15 237	9 645	8 971
Web technicians	195	269	148	98
Data entry clerks	532	701	351	345
ICT and HR managers / marketing specialists				
Human resource managers	1 702	2 824	2 293	1 453
ICT service managers	4 835	8 183	4 292	4 414
Advertising and marketing professionals	9 661	17 304	8 811	9 375
Rest of occupations	784 793	1 300 964	784 910	746 736
TOTAL	892 922	1 477 456	889 747	851 274

Source: OECD calculations based on Lightcast data.

Annex 4.B. The labour market demand for data scientists and data engineers in Canada and the United Kingdom

Annex Figure 4.B.1. Evolution of online postings for data scientists and data engineers in Canada and the United Kingdom

Index (2012 = 100)



Source: OECD calculations based on Lightcast data.

Notes

[1] Randstad Research Italy (RRI) (n.d.[7]) is a research centre of the Randstad group, born in 2019. The institute undertakes a number of qualitative and quantitative surveys, case studies and sector studies, analysing the supply and demand in the labour market and the future skills needs.

[2] These fall under the six-digit SOC category of web developers. This latter is also the corresponding occupation for EU countries where, due to the more aggregated occupational taxonomy, information on UI/UX designers/developers cannot be directly extracted, but more broadly that related to web developers.

[3] In fact, the EU occupations within this group belong to the ISCO (one-digit) groups 3 and 4, and to Lightcast (two-digit) groups 43 (this is the case for two out of the three occupations within this group).

[4] In the Anglophone countries' taxonomy.

[5] In EU countries' taxonomy.

[6] These shares should not be interpreted as the weight of digital occupations in the labour market, as it is just a fraction of those (20 for Canada, the United Kingdom, and the United States; 17 for Singapore; and 14 for EU countries) that are under study.

[7] Annex 4.A provides more detail in the levels of OJPs for each of the ten countries analysed.

[8] The lowest shares for this occupational group are in Italy (21%), and Canada, Singapore and Spain (22%). On the other hand, in France and Germany this occupational group is relatively more important, as it represents 30% and 35% of the total selected digital OJPs, respectively.

[9] Notice that differences in the results across EU and Anglophone countries may be partly driven by the different occupational classifications used in the two sets of countries which are likely to affect results particularly in occupational groups with fewer sub-categories.

[10] As noted in the OECD's Employment Outlook 2021 (OECD, 2021[6]) employment in several routine and low-skilled occupations, as is the case for data entry clerks, "is expected to decline in the short term and to further deteriorate in the long-run".

[11] In the United Kingdom, the increase in OJPs for data scientists has also been strong, going from merely 179 postings in the initial year of observation to more than 11 000 new postings in 2017, a figure that is 60 times larger in the time span of only 5 years. After then, postings declined but have lately recovered, being back again at levels close to 11 000 in 2021. More details on the evolution of OJPs for data scientists and data engineers for the UK, as well as Canada, can be found in Annex 4.B.

[12] In particular, their size has increased 2.6 times relative to 2012.

5 The skill profiles and the competences of workers in digital occupations

This chapter presents the detailed skill profiles of the selected digital occupations by highlighting the emergence of the demand for specific digital technologies across all labour markets. The information on the skill profiles presented in this chapter is based on the analysis of employers' demands contained in millions of job postings collected from the internet in ten countries: Belgium, Canada, France, Germany, Italy, the Netherlands, the United Kingdom, the United States, Singapore and Spain. The relevance of the skills for the occupations under exam is empirically derived by applying machine learning techniques and natural language processing algorithms to the text information contained in job postings with the aim to detect patterns in the demands of employers.

The rapid pace of the digital transformation is not only leading to a significant increase in the demand for professionals working in the digital world (see Chapter 4) but it is also changing the way the labour market functions and the skills that are required to perform jobs and tasks within those occupations. In order to adapt to these changes, businesses require the workforce to acquire and maintain adequate digital skills throughout their life course (OECD, 2021[1]). This is especially true in occupations like the digital ones, where tasks are changing at an even faster pace than those in the rest of the economy, and where new technologies are constantly adopted in productive processes and services.

Against this backdrop, a key challenge for policy makers and firms is that of clearly identifying the digital skill profiles of occupations that are in high demand so as to ensure that the labour force is well-prepared[1] for jobs where the use of technology is becoming increasingly central.

Up until now, the availability of granular information on skill demands in digital occupations was scarce and the information available at a relatively high-level of aggregation. Previous skills studies, for instance, were mostly based on the use of surveys collected with significant lags and aggregated up into broad skill categories whose use to create skill profiles was fairly high-level.

The use of the information contained in online job postings for labour market intelligence offers now the possibility to exploit the rich skills information of millions of job postings to understand companies' current needs in terms of tasks and skills at a very disaggregated level.

This chapter leverages the information contained in OJPs and applies machine learning techniques to identify the skill profiles (i.e. the most relevant skills) of the digital occupations covered in this report.

The remainder of this chapter presents the skill profiles of digital occupations showing the top five most relevant skills and knowledge areas associated with these occupations, which are broken down into the four occupational groups as shown earlier in Figure 4.1 of Chapter 4.

5.1. Computer and data analysts' skill profiles

Chapter 4 has shown the significant increase in the number of job postings published online for computer and data analysts' occupations. From a skill demands' stand point, computer occupations such as data engineers, data and computer scientists, data mining analysts or system analysts share a variety of digital skill requirements that are, in turn, in high demand.

The analysis of OJPs shows, for instance, that data warehousing skills (i.e. the process of collecting and managing data from different sources to provide meaningful business analyses) are very relevant in job postings for data mining analysts and data engineers in Canada, as well as in the United States.

Data warehousing skills are central to a wide variety of businesses, as the collection of raw data is increasing significantly across all sectors and firms need to find solutions to store and analyse those data to plan marketing strategies, production processes and for efficient use of internal resources. The ability of managing large quantities of data is used in diverse areas, from the health care sector (e.g. by creating reports about patients or predict the results of a certain treatment) to the aeronautic industry (e.g. by examining the profitability of the different routes offered). Database management systems skills, similarly to data warehousing skills, are very relevant for database designers and administrators. Results from OJPs show these skills being very relevant in virtually all EU countries covered in this study and in particular in Italy, the Netherlands, Germany and Belgium, where they are amongst the top 5 skills by relevance in fast growing occupations such as database designers and administrators.

Occupations and jobs do, however, require a rather heterogeneous mix of skills to be performed and online job postings highlight how skills, knowledge types and technologies actually merge in the overall skills demands of employers.

Results show, for instance, that database management and warehousing skills are required jointly with several other data-related and data-analytics skills in computer occupations. An interesting example is that of the skills demands in the area of cloud technologies which are tightly linked to database management tasks and show prominently as relevant skills in digital occupations (see Box 5.1).

Box 5.1. Cloud computing and digital skill demands

In general terms, cloud computing enables on-demand computing services such as data storage, database, networking, server, analytics, and intelligence through the Internet. It also enables users and businesses to operate from anywhere without needing to resort to a local storage device or additional networking infrastructure. Looking at trends, over the past three years, the market for cloud computing has grown tremendously, as its importance was further reinforced with the COVID-19 crisis and the necessity to telework for an important part of the workforce. Results from online job postings show that the knowledge of how to operate cloud technologies is key for database and network professionals in France, Germany and the Netherlands and that this knowledge requirement is usually required along with the the ability of managing and administering ICT data architecture using specific technologies such as Azure (a cloud computing service operated by Microsoft for application management via Microsoft-managed data centres) or VMware (a cloud computing and virtualisation technology).

The ability to analyse big data with new statistical tools also plays a central role in a variety of computer-related occupations across countries. The words “big data” usually refer to large, complex datasets, mostly arising from new and unstructured data sources such as those collected by smartphones, mobile applications as well as from interconnected devices used in production. Compared to traditional data, big data are more voluminous, implying that specific software and statistical methods need to be used to analyse them. Results from OJPs show that machine learning and artificial intelligence are the key complementary skills to big data and that they are highly relevant in jobs where the knowledge of big data is also important such as computer and data analysis occupations.

An emerging trend in the skill demands of digital occupations is also the increasing relevance of open source platforms and software libraries such as Tensorflow. OJPs’ data show that Tensorflow (an open-source platform that allows to operate machine learning and artificial intelligence in a variety of different contexts), is particularly relevant for computer scientists and data scientists in Canada, the United Kingdom and the United States. Tensorflow was originally developed by Google and contains a number of tools, libraries and community resources that allow users to build machine learning-powered applications used in most digital services today.

Within the group of computer occupations, particular attention should be paid to cyber / information security engineers / analysts who require a rather specific skill bundle that sets them apart from most of the other computer occupations. Data from online job postings reveals, for instance, that employers in Canada, Singapore, United Kingdom and the United States seek cybersecurity professionals with a strong knowledge of information security and network security, as well as of IT management. Along with these very specific technical skills, cybersecurity professionals are also expected to know standards, guidelines and best practices to manage cybersecurity risks in firms and organisations such as, for instance, the NIST Cybersecurity Framework (a set of guidelines published by the US National Institute of Standards and Technology (NIST) for mitigating an organisation’s cybersecurity risks by providing a taxonomy on cybersecurity outcomes and a methodology to assess and manage them).[2]

5.2. Software developers, programmers and engineers' skill profiles

Analysis of the information contained in OJPs shows that a number of occupations in the area of software development and programming requires the knowledge of Java. Java is a general-purpose programming language and computing platform that allows users to run code on all platforms that support Java without needing to recompile the code. Results show that the knowledge of Java is particularly relevant for software developers and programmers in Germany, where Java lies within the top 5 most demanded skills for web and multimedia developers, applications programmers and software developers. Similarly, knowledge of Java is key for software developers / engineers and computer programmers in Canada, Singapore, the United Kingdom and the United States, as well as computer systems engineers and web developers. In Singapore, on top of software developers/ engineers, the usage of Java is also within the top 5 most relevant skills for UI / UX designers / developers, computer programmers, computer systems engineers / architects.

In addition to produce code and programming, the tasks of software developers also include the design of software systems. In practice, most software developers build targeted codes and scripts to achieve a specific objective which, in complex systems and organisations, can be difficult to communicate to other co-workers and to manage practically. In this context, the usage of Unified Modelling Language (UML) is becoming increasingly relevant. ULM is "*a standardised modelling language consisting of an integrated set of diagrams, developed to help system and software developers for specifying, visualizing, constructing, and documenting the artefacts of software systems, as well as for business modelling and other non-software systems*" (Visual Paradigm, n.d.[2]). The analysis of OJPs shows that the knowledge of UML is key to the tasks of software engineers across EU countries and it is particularly relevant in occupations such as applications programmers. Among the different UML-related software, the knowledge of Middleware (a software that allows communication and data management in distributed applications, facilitating programmers or software developers the task of implementing communication input or output to focus on the specific purpose of their application) shows up with much relevance in online job postings for software developers jobs in Canada, United States, the United Kingdom and Singapore.

Recent studies (OECD, 2021[3]) have also highlighted the role that automation is already playing across labour markets. Digital occupations are very much linked to the design and implementation of automation solutions. Data from OJPs shows that the knowledge of computer-aided engineering (CAE) (i.e. computer software to simulate performance with the aim of improving product designs or aid in the resolution of engineering problems) is required for electronics engineers and ICT operations technicians in several EU labour markets (Belgium and Germany for instance). The knowledge of CAE is also usually required along with skills in technical drawing software as well as with knowledge of automation technologies and the internet of things (IoT).

Interestingly, for a subset of software-related occupations (i.e. web designers), some business and sales-related skills are emerging as being very important. In the United States, for instance, web developers are typically required to know about online advertising and online marketing. Web analytics are also very relevant to web designers in Singapore as well as knowledge of copywriting in Canada. Results seems to suggest that the job of web designers is evolving in the direction of mixing different skill sets and tasks whose only part are related to programming and technical, while others relate to the ability of the web designer of creating a marketable final product for its customers.

For the Anglophone countries covered in this study, where occupational and skill data is more disaggregated than for the EU, the information in OJPs allows to identify the most relevant skills for UI / UX designers / developers directly. In the United States, for instance, UI/UX designers and developers are required to have strong knowledge of user research (i.e. the systematic study of target users and their requirements with the aim of adding realistic contexts and insights to design processes). This skill is usually sought along with knowledge of web analytics (the measurement, collection, analysis, and reporting of web data to understand and optimise web usage) and version control (the ability to manage changes to computer programs, documents, large web sites, or other collections of information).

5.3. ICT technicians and data entry clerks' skill profiles

The digital transition involves a series of different job roles, some of which carry out mid to lower-skill digital tasks that are, nonetheless, key for IT systems to work effectively. Amongst those professionals, there are those who work on the technical aspects of the IT infrastructure, such as web technicians and computer support specialists and operators and others that instead are employed in the more mechanical tasks of data ingestion and control, such as the data entry clerks.

While most digital occupations are usually high-skilled ones and require extensive expertise, some digital professions involve a certain degree of routine tasks and are lower skilled. Data entry clerks is one of those examples. Data clerks do interact with digital technologies but they do so in a routine-based and sometime repetitive manner. Among the tasks of data entry clerk there is the transferring of data from paper formats into computer files or database systems. Data entry clerk do usually type in data provided directly from customers and create spreadsheets with large numbers of figures.

As of now, the analysis of the OJPs shows that the most relevant skills for data entry clerks are, as expected, of a very different nature compared to the more technical (non-routine) ones analysed up until now. For instance, the ability to typing effectively is a very relevant skill for data entry clerks in Canada and the United Kingdom, along with dictation.

As new technologies start to automatise some of these tasks, jobs for data entry clerks may either decline in volume[3] or radically change the nature of some of the tasks that are currently carried out by those employed in these occupations. Recent developments in speech recognition technologies already allow individuals to use note-taking software that is more accurate and rapid than well-trained humans taking dictation. This is not to say that "note-taking" skills will disappear immediately. In the short term, Word processors and typists will probably need to learn how to interact with machines and software programmes to "teach" them new terms and flag the most difficult words. As a confirmation of this, data from OJPs in Singapore shows that data entry clerks are required to manage specific software, such as MYOB (accounting software). Sage 100 (business management software) is instead key in the United States, or SAP R/3 in France and the Netherlands. In the EU, data show that Microsoft Excel (in the United Kingdom), Microsoft Dynamics (in Belgium) and Microsoft Office (in Spain) are still key for data entry clerks and very much sought by employers for those job roles.

Analysis of OJPs shows that web technicians in Belgium, France, Germany, the Netherlands and Spain are widely required to design User Interfaces (UIs) which are needed for final users to operate complex IT systems. The goal of UIs is to make the interaction between human users and computers, websites or applications easy and intuitive, ensuring that users require minimum effort to receive the maximum desired outcome. Interestingly, the ability to design UI is also relevant in other occupations related to software development and programming, such as web and multimedia developers (in France and the Netherlands) or applications programmers (in Germany). Those latter occupations are indeed relatively high-skill, showing how certain skill requirements do bridge between routine and more high-level cognitive skills.

5.4. ICT and HR managers / marketing specialists' skill profiles

As digital tools and technologies are increasingly adopted by businesses and organisations, managerial positions geared towards the supervision of digital processes (and of teams devoted to operate digital technologies) are also on the rise in different organisations and firms.

When looking at skill profiles, it is well known that managerial positions require a wide variety of soft skills. Digital managers are not the exception, despite mixing those skills with others that are much more technical in nature. The analysis of OJPs shows, for instance, that Chief Information Officers / directors of IT and ICT services managers are usually called to have managerial skills (e.g. manage a team) and strategic thinking. More in detail, IT management skills (i.e. the ability to manage the Information Technology resources of a firm in accordance with its needs and priorities) and agile management (i.e. practices that include requirements discovery and solutions improvement through the collaborative effort of self-organising and cross-functional teams) or Waterfall Development Process (i.e. the sequential development process that flows like a waterfall through all phases of a project such as analysis, design, development, and testing) are very relevant for Chief Information Officers.

Interestingly, in addition to those already mentioned, in the United States, Chief Information Officers are also increasingly required to have knowledge of artificial intelligence, while in Germany, they are widely required knowledge of supply chain principles. In Singapore, knowledge of intellectual property rights is also relevant for Chief Information Officers while in Canada, they are required to be able to work on effective business solutions.

Human resources managers fall within the broader group of managerial occupations that are becoming increasingly digital. Similarly to Chief Information Officers, human resources managers are required to have soft skills such as being able to manage "employee relations". In the European countries analysed, human resources managers are expected to be able to build business relationships, make improvements to work activities as well as manage personnel.

Beyond soft skills, other more technical skills are relevant for human resources managers. In the United States, for instance, they are expected to know UltiPro Payroll, a cloud-based payroll service, which automates the payroll of a company's workforce.

Marketing occupations are also becoming increasingly digital. Marketing specialists and advertising and marketing professionals are expected to know about online marketing, online advertising or web analytics. In the United Kingdom and the United States, OJPs show that the knowledge of marketing automation solutions such as Pardot is becoming increasingly important, as well as knowledge of Search Engine Optimisation (SEO).

Table 5.1. Canada: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Cyber / Info. Security Eng. / Analyst	Nist Cybersecurity Framework	Network Security	Information Security	Microsoft Certified Professional Azure	IT Management
Data / Data Mining Analyst	Data Visualization	Data Mining	Data Analysis	Microsoft Power Bi	Data Warehousing
Database Administrator	Data Warehousing	Apache Hive	Database Administration	Oracle	Distributed Computing
Data Engineer	Data Warehousing	Distributed Computing	Big Data	Apache Hive	Java
Computer Scientist	Machine Learning	Tensorflow	Data Science	Artificial Intelligence	Distributed Computing
Data Scientist	Data Science	Machine Learning	Apache Hive	Tensorflow	Big Data
Systems Analyst	IT Management	Java	Middleware	SAP	Oracle
Software developers, programmers and engineers					
UI / UX Designer / Developer	User Research	Design Thinking	Bootstrapping	Software Quality Assurance	Web Development
Web Designer	Web Development	Multimedia	Online Marketing	Online Advertising	Creative Design
Web Developer	Web Development	Bootstrapping	Typescript	Java	Version Control
Computer Programmer	Software Quality Assurance	Middleware	Bootstrapping	Java	Web Servers
Computer Systems Eng. / Architect	Java	Cloud Computing	Firmware	Distributed Computing	Middleware
Software Developer / Eng.	Java	Bootstrapping	Version Control	Software Quality Assurance	Bitbucket
Hardware Engineer	Firmware	SDN	Schematic Diagrams	Border Gateway Protocol	Software Quality Assurance
ICT technicians and data entry clerks					
Computer Support Specialist	Help Desk Support	Technical Support	IT Management	Middleware	Web Servers
Computer Operator	Business English	Traffic Management	Equipment Operation	Transaction Processing	Nginx
Data Entry Clerk	Typing	Dictation	Office Management	Business English	Telephone Skills
ICT and HR managers / marketing specialists					
Marketing Specialist	Online Marketing	Advertising	Web Analytics	Marketing Management	Online Advertising
Chief Information Officer / Director of IT	IT Management	Waterfall Development Process	Software Quality Assurance	Business Solutions	Budget Management
Human Resources Manager	Employee Relations	SAP SuccessFactors	Business Consulting	Employee Training	Business Strategy

Source: OECD calculations based on Lightcast data.

Table 5.2. Singapore: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Cyber / Info. Security Eng. / Analyst	Information Security	Network Security	IT Management	Middleware	Project Management
Data / Data Mining Analyst	Data Science	Machine Learning	Data Analysis	Big Data	Database Administration
Database Administrator	Database Administration	Data Warehousing	Data Management	Business Intelligence	Big Data
Systems Analyst	SAP	Business Solutions	Java	Data Warehousing	Code Reviews
Software developers, programmers and engineers					
UI / UX Designer / Developer	Web Development	Bootstrapping	Design Thinking	Java	Version Control
Web Designer	Web Development	Online Marketing	Web Analytics	Multimedia	Online Research
Web Developer	Web Development	Bootstrapping	Version Control	Java	Software Quality Assurance
Computer Programmer	Java	Web Development	Software Quality Assurance	Version Control	Middleware
Computer Systems Eng. / Architect	Microsoft Windows	Technical Support	IT Management	Middleware	Java
Software Developer / Eng.	Java	Web Development	Version Control	Software Quality Assurance	Code Reviews
Hardware Engineer	Firmware	Product Development	Simulation	Configuration Management	Technical Support
ICT technicians and data entry clerks					
Computer Support Specialist	Technical Support	Microsoft Windows	Configuration Management	Troubleshooting Technical Issues	Middleware
Computer Operator	Configuration Management	Microsoft Windows	IT Management	Technical Support	SAP
Data Entry Clerk	Administrative Support	Myob	Telemarketing	Inventory Maintenance	Typing
ICT and HR managers / marketing specialists					
Marketing Specialist	Online Marketing	Marketing Management	Brand Management	Web Analytics	Social Media Tools
Chief Information Officer / Director of IT	IT Management	Intellectual Property	Strategic Thinking	Configuration Management	Robotics
Human Resources Manager	Employee Relations	Talent Management	Business Management	Employee Training	Performance Management

Source: OECD calculations based on Lightcast data.

Table 5.3. United Kingdom: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
			Computer and data analysts / administrators		
Cyber / Info. Security Eng. / Analyst	NIST Cybersecurity Framework	Network Security	Information Security	Juniper Networks	IT Management
Data / Data Mining Analyst	Microsoft Power Bi	Operations Analysis	Data Warehousing	Data Visualisation	Business Intelligence
Database Administrator	Database Administration	Data Warehousing	Oracle	Unix Platforms	Apache Impala
Data Engineer	Distributed Computing	Data Warehousing	Big Data	Business Intelligence	Apache Impala
Computer Scientist	Electronics Industry Knowledge	Machine Learning	Artificial Intelligence	Tensorflow	Mechanical Engineering
Data Scientist	Data Science	Machine Learning	Unsupervised Learning	Tensorflow	Distributed Computing
Systems Analyst	SAP	IT Management	Business Intelligence Software	Oracle	Cloud Computing
			Software developers, programmers and engineers		
UI / UX Designer / Developer	User Research	Web Development	Typescript	Software Quality Assurance	Kibana
Web Designer	Web Development	User Research	Digital Design	Copywriting	Online Marketing
Web Developer	Web Development	Laravel	Typescript	Version Control	Software Quality Assurance
Computer Programmer	Version Control	Java	Middleware	Web Servers	Distributed Computing
Computer Systems Eng. / Architect	IT Management	Juniper Networks	Web Servers	Java	Cloud Computing
Software Developer / Eng.	Java	Typescript	Version Control	Web Servers	Knockout Js
Hardware Engineer	Electronics Industry Knowledge	Schematic Diagrams	Machine Learning	Solidworks	Simulation
			ICT technicians and data entry clerks		
Computer Support Specialist	IT Management	Technical Support	Microsoft Windows	Help Desk Support	Network Switches
Computer Operator	Deskside Support	Virtual Local Area Networks	Network Switches	Help Desk Support	Systems Monitoring
Data Entry Clerk	Typing	Microsoft Excel	Data Management	Database Administration	Computer Literacy
			ICT and HR managers / marketing specialists		
Marketing Specialist	Pardot	Marketing Management	Online Marketing	Online Advertising	Product Management
Chief Information Officer / Director of IT	IT Management	Network Security	Virtual Local Area Networks	Olas	Network Switches
Human Resources Manager	Employee Relations	Human Resources Systems	Talent Management	Tupe	Business Strategy

Source: OECD calculations based on Lightcast data.

Table 5.4. United States: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Cyber / Info. Security Eng. / Analyst	NIST Cybersecurity Framework	Information Security	Network Security	Fidelis Solution/ software	Application Security Testing Ecosystem
Data / Data Mining Analyst	Data Visualization	Data Warehousing	Business Intelligence Software	Apache Hive	Java
Database Administrator	Data Warehousing	Haproxy	Jaspersoft	Middleware	Red Hat Wildfly
Data Engineer	Distributed Computing	Data Warehousing	Apache Hive	Big Data	Java
Computer Scientist	Machine Learning	Tensorflow	Artificial Intelligence	Caffe Deep Learning Framework	Firmware
Data Scientist	Data Science	Machine Learning	Tensorflow	Data Visualization	Data Warehousing
Systems Analyst	Data Collection	IT Management	Ehcache	Data Warehousing	SAP Solman
Software developers, programmers and engineers					
UI / UX Designer / Developer	User Research	Web Analytics	Software Quality Assurance	Resteasy	Version Control
Web Designer	Script Writing	Web Analytics	Pc Platform	SEO Copywriting	Creative Design
Web Developer	Typescript	Laravel	Resteasy	Java	Version Control
Computer Programmer	Resteasy	Java	Spring Rest	Middleware	Haproxy
Computer Systems Eng. / Architect	Firmware	IT Management	Red Hat Wildfly	Resteasy	Wildfly
Software Developer / Eng.	Java	Version Control	Data Warehousing	Middleware	Microsoft Certified Professional Azure
Hardware Engineer	Firmware	Emulation	Digital Design	Analog Design	DxDesigner
ICT technicians and data entry clerks					
Computer Support Specialist	Hardware Asset Management	Help Desk Support	Airwatch	Technical Support	Enterprise Mobility Management
Computer Operator	Communications Industry Security	Help Desk Support	Emc Vnx	Script Writing	Haproxy
Data Entry Clerk	Sage 100	Inventory Metrics	Refunding Money	Oracle Toad	Credit and Collection Call Response
ICT and HR managers / marketing specialists					
Marketing Specialist	Online Marketing	Marketing Management	Web Analytics	SEO Copywriting	Pardot
Chief Information Officer / Director of IT	IT Management	Haproxy	Artificial Intelligence	Talend Data Integration	IBM Bluemix
Human Resources Manager	Human Resources Systems	Employee Relations Investigations	Employee Relations	State Payroll Regulations	Ultipro

Source: OECD calculations based on Lightcast data.

Table 5.5. Belgium: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
			Computer and data analysts / administrators		
Database and network professionals n.e.c.	Cloud Technologies	Administer ICT System	ICT Communications Protocols	Manage Database	ICT System Programming
Database designers and administrators	Database Management Systems	Manage Database	Unified Modelling Language	Administer ICT System	Maintain ICT System
Systems analysts	Integration Management	ABAP	Administer ICT System	Database Management Systems	Manage Database
			Software developers, programmers and engineers		
Web and multimedia developers	Use Software Design Patterns	Use Query Languages	Use Markup Languages	Web Programming	Analyse Software Specifications
Applications programmers	Use Query Languages	Unified Modelling Language	Use Software Design Patterns	Manage Database	Web Programming
Software developers	Unified Modelling Language	Use Software Design Patterns	Manage ICT Data Architecture	Administer ICT System	Java
Electronics engineers	CAE Software	Use Technical Drawing Software	Automation Technology	Computer Technology	Electricity
			ICT technicians and data entry clerks		
Web technicians	Use Markup Languages	Design User Interface	Use Query Languages	Web Programming	Administer ICT System
ICT user support technicians	Administer ICT System	Maintain ICT System	ICT System Programming	Windows Server	Use ICT Hardware
ICT operations technicians	Administer ICT System	Business ICT Systems	CAE Software	Microsoft Dynamics	Maintain ICT System
Data entry clerks	Microsoft Dynamics	Prioritise Tasks	Adjust Priorities	Adapt to Change	ABAP
			ICT and HR managers / marketing specialists		
ICT service managers	Business ICT Systems	ICT System Programming	Administer ICT System	Manage a Team	Agile
Advertising and marketing professionals	Plan Digital Marketing	Marketing Department Processes	Marketing	Social Media Marketing Techniques	Digital Marketing Techniques
Human resource managers	Human Resource Management	Personnel Management	Office Administration	Manage a Team	Build Business Relationships

Note: For data entry clerks, ambiguous skill terms have been excluded from the results in the table and replaced with the closest skill term in the relevance ranking.
Source: OECD calculations based on Lightcast data.

Table 5.6. France: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Database and network professionals n.e.c.	Big Data	Cloud Technologies	Scripting	Administer ICT System	Use Scripting Programming
Database designers and administrators	Oracle Application Development Framework	Database Management Systems	Manage Database	Use Software Design Patterns	Business ICT Systems
Systems analysts	Administer ICT System	Business ICT Systems	Scripting	Big Data	Windows Server
Software developers, programmers and engineers					
Web and multimedia developers	Use Query Languages	PHP	AngularJS	Web Programming	Design User Interface
Applications programmers	Unified Modelling Language	Scripting	AngularJS	Manage Project Metrics	Agile Project Management
Software developers	Use Query Languages	Database Management Systems	Unified Modelling Language	Maintain ICT System	MySQL
Electronics engineers	Use ICT Hardware	Scripting	Use Scripting Programming	Computer Technology	Simulation
ICT technicians and data entry clerks					
Web technicians	Use Query Languages	Design User Interface	AngularJS	JavaScript Framework	PHP
ICT user support technicians	Windows Server	Manage ICT Virtualisation Machines	Administer ICT System	Maintain ICT System	ICT Networking Hardware
ICT operations technicians	Automation Technology	Use Software Design Patterns	Analyse Software Specifications	Report Analysis Results	SAP R/3
Data entry clerks	SAP R/3	Sas Data Management	Sas Language	Statistical Analysis System Software	Welding Techniques
ICT and HR managers / marketing specialists					
ICT service managers	Business ICT Systems	Administer ICT System	Maintain ICT System	Windows Server	Supply Chain Principles
Advertising and marketing professionals	Plan Digital Marketing	Marketing Department Processes	Marketing	Social Media Marketing Techniques	Sales Strategies
Human resource managers	Personnel Administration	Accounting	Make Improvements to Work Activities	Accounting Techniques	Analytics

Source: OECD calculations based on Lightcast data.

Table 5.7. Germany: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Database and network professionals n.e.c.	Big Data	Cloud Technologies	Azure	VMware	Administer ICT System
Database designers and administrators	Database Management Systems	Oracle Application Development Framework	Manage Database	Big Data	Oracle
Systems analysts	Manage Database	Administer ICT System	Big Data	Use Scripting Programming	Oracle Application Development Framework
Software developers, programmers and engineers					
Web and multimedia developers	Web Analytics	Java	Administer ICT System	Computer Programming	Database Management Systems
Applications programmers	Java	Design User Interface	Database Management Systems	Use Software Design Patterns	Web Programming
Software developers	Java	Administer ICT System	Git	Database Management Systems	Tools for Software Configuration Management
Electronics engineers	IoT	Algorithms	Hardware Components	Use ICT Hardware	CAE Software
ICT technicians and data entry clerks					
Web technicians	Web Analytics	Design User Interface	HTML	Administer ICT System	Java
ICT user support technicians	Administer ICT System	Unix	Manage ICT Change Request Process	Business ICT Systems	ICT Infrastructure
ICT operations technicians	Administer ICT System	Oracle Application Development Framework	Azure	Business ICT Systems	VMware
Data entry clerks	Satisfy Customers	Manage Warehouse Inventory	Manage System Security	Manage Warehouse Operations	Electricity principles
ICT and HR managers / marketing specialists					
ICT service managers	Business ICT Systems	Web Analytics	Administer ICT System	Manage a Team	Supply Chain Principles
Advertising and marketing professionals	Plan Digital Marketing	Sales Strategies	Web Analytics	Customer Segmentation	Marketing Management
Human resource managers	Human Resource Management	Labour Legislation	Service Management	Manage a Team	Build Business Relationships

Note: For data entry clerks, some ambiguous skill terms have been excluded from the results in the table and replaced with the closest skill term in the relevance ranking.
Source: OECD calculations based on Lightcast data.

Table 5.8. Italy: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Database and network professionals n.e.c.	Integration Management	ICT Project Management Methodologies	Administer ICT System	Use Scripting Programming	ICT Communications Protocols
Database designers and administrators	Database Management Systems	Oracle Application Development Framework	SQL Server	Manage Database	Oracle
Systems analysts	ABAP	Integration Management	Administer ICT System	ICT System Programming	Analysis
Software developers, programmers and engineers					
Web and multimedia developers	Use Markup Languages	Use Query Languages	AngularJS	World Wide Web Consortium Standards	Web Programming
Applications programmers	Mobile Device Software Frameworks	Mobile Operating Systems	Use Software Design Patterns	Analyse Software Specifications	GitHub
Software developers	AngularJS	Unified Modelling Language	Use Software Design Patterns	World Wide Web Consortium Standards	Analyse Software Specifications
Electronics engineers	Electronics	Electricity	Mechanics	Computer Technology	Use ICT Hardware
ICT technicians and data entry clerks					
Web technicians	Use Markup Languages	Web Programming	JavaScript Framework	Use Query Languages	World Wide Web Consortium Standards
ICT user support technicians	ICT System Programming	Use ICT Hardware	Windows Server	ICT Communications Protocols	Administer ICT System
ICT operations technicians	Use Software Design Patterns	Analyse Software Specifications	CAE Software	ICT Communications Protocols	Automation Technology
ICT and HR managers / marketing specialists					
ICT service managers	Business ICT Systems	Administer ICT System	Manage a Team	ICT Project Management Methodologies	ICT System Programming
Advertising and marketing professionals	Plan Digital Marketing	Brand Marketing Techniques	Design Campaign Actions	Develop Campaigns	Web Analytics
Human resource managers	Personnel Management	Human Resource Management	Build Business Relationships	Manage Budgets	Conclude Business Agreements

Note: Results for data entry clerks have been excluded from the table due to insufficient information for the semantics analysis.
Source: OECD calculations based on Lightcast data.

Table 5.9. The Netherlands: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Database and network professionals n.e.c.	Azure	Cloud Technologies	Scripting	Manage ICT Data Architecture	Manage ICT Virtualisation Machines
Database designers and administrators	Database Management Systems	Manage Database	Unified Modelling Language	Use Query Languages	PHP
Systems analysts	Agile	Integration Management	Manage Database	Scripting	Use Scripting Programming
Software developers, programmers and engineers					
Web and multimedia developers	Design User Interface	PHP	Use Query Languages	Administer ICT System	Use Software Design Patterns
Applications programmers	Unified Modelling Language	Use Software Design Patterns	Database Management Systems	Manage ICT Data Architecture	Manage Database
Software developers	Use Software Design Patterns	Unified Modelling Language	PHP	Manage Database	Web Programming
Electronics engineers	Plan Manufacturing Processes	Use Technical Drawing Software	Automation Technology	Hardware Components	Use ICT Hardware
ICT technicians and data entry clerks					
Web technicians	Wordpress	Web Analytics	Maintain ICT System	Social Networking	Use Query Languages
ICT user support technicians	Administer ICT System	Maintain ICT System	Use Scripting Programming	ICT System Programming	Scripting
ICT operations technicians	Administer ICT System	Perform Backups	Business ICT Systems	Provide Documentation	Use Spreadsheets Software
Data entry clerks	Proactivity	Office Administration	SAP R/3	Work Independently	Sales Argumentation
ICT and HR managers / marketing specialists					
ICT service managers	Business ICT Systems	ICT System Programming	Agile	Administer ICT System	Build Business Relationships
Advertising and marketing professionals	Plan Digital Marketing	Digital Marketing Techniques	Social Media Marketing Techniques	Sales Promotion Techniques	Sales Strategies
Human resource managers	Human Resource Management	Personnel Management	Office Administration	Give Advice to Others	Office Software

Source: OECD calculations based on Lightcast data.

Table 5.10. Spain: Digital occupations and top skills set

	Skill 1	Skill 2	Skill 3	Skill 4	Skill 5
Computer and data analysts / administrators					
Database and network professionals n.e.c.	Big Data	Use Scripting Programming	Administer ICT System	Unified Modelling Language	Agile Project Management
Database designers and administrators	Oracle Application Development Framework	Database Management Systems	Windows Server	Maintain ICT System	Manage Database
Systems analysts	ABAP	Big Data	Integration Management	Administer ICT System	Oracle Application Development Framework
Software developers, programmers and engineers					
Web and multimedia developers	AngularJS	Backend	JavaScript Framework	Use Query Languages	World Wide Web Consortium Standards
Applications programmers	Mobile Device Software Frameworks	Mobile Operating Systems	iOS	AngularJS	Backend
Software developers	Unified Modelling Language	AngularJS	Backend	iOS	World Wide Web Consortium Standards
Electronics engineers	Computer Technology	Engineering Principles	Automation Technology	Robotics	Communication Principles
ICT technicians and data entry clerks					
Web technicians	Use Markup Languages	Create Software Design	Backend	Design User Interface	HTML
ICT user support technicians	Windows Server	Administer ICT System	Computer Technology	Maintain ICT System	Unix
ICT operations technicians	Use Software Design Patterns	Mobile Device Software Frameworks	Use Microsoft Office	iOS	Unified Modelling Language
Data entry clerks	Use Microsoft Office	Use Office Systems	English	Use Creative Suite Software	Customer service
ICT and HR managers / marketing specialists					
ICT service managers	Business ICT Systems	Administer ICT System	Office Administration	Computer Technology	Database Management Systems
Advertising and marketing professionals	Plan Digital Marketing	Marketing Department Processes	Digital Marketing Techniques	Web Analytics	Social Media Management
Human resource managers	Brainstorm Ideas	Project Management	Economics	Personnel Management	Business Processes

Note: For data entry clerks, some ambiguous skill terms have been excluded from the results in the table and replaced with the closest skill term in the relevance ranking.
Source: OECD calculations based on Lightcast data.

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Notes

[1] More broadly, there are important concerns as to the way technological change might impact on the low skilled or those with poor digital skills (OECD, 2021[3]).

[2] The guide feeds from existing standards, guidelines and practices.

[3] Jobs for data entry clerks and Word processors and typists are also expected to decline by 20% and 36% in Canada (by 2028) and the United States (by 2029) respectively. Source: (Government of Canada, n.d.[4]) and (US Bureau of Labor Statistics, 2020[5]).

6 The diffusion of digital skill demands in labour markets

This chapter presents indicators of the pace by which the demand for digital skills has been permeating labour markets across ten countries: Belgium, Canada, France, Germany, Italy, the Netherlands, the United Kingdom, the United States, Singapore and Spain. The chapter focuses on the speed by which advanced data analysis skills, programming skills, automation and Internet of Things (IoT) related skills, as well as cybersecurity and business and sales digital skill demands have been diffusing across occupations over time. Results in this chapter show the significant diffusion of most digital skills across the demand of employers and provides information on areas where bottlenecks and labour market gaps are likely to emerge.

The use of digital technologies has increased exponentially in recent decades and their applications can now be found in a variety of different sectors of the labour market, going from mechanics and manufacturing to services and health care. The computing power of increasingly smaller digital devices such as mobile phones and tablets has allowed the development and implementation of a range of new digital services that are now channelled through mobile applications.

Digital services like Spotify or Netflix, just to mention some amongst the most famous contemporary digital platforms, have revolutionised the way in which music and entertainment are delivered to final customers. These digital services rely not only on the idea of bringing music and entertainment content online but, very importantly, on the specific technical development and deployment of digital technologies such as cloud computing, data analysis as well as machine learning. Netflix, for instance, uses adaptive bitrate streaming technology[1] to adjust video and audio quality to match the broadband connection speed and network conditions of the viewers. These technical aspects of the service, in turn, are only possible thanks to the development of cloud storage that is used to save millions of terabytes of information online. Cloud computing itself, however, runs on a worldwide network of secure data-centres, which are regularly upgraded to the latest generation of fast and efficient computing hardware. Operating such complex architectures requires specific digital skills that go from database management skills to software development (usually also called DevOps) to the knowledge of data-oriented programming languages like Ruby, Python and Perl.

While the ones mentioned above are just examples of the widespread adoption of digital technologies in labour markets, it is clear that individuals and workers are nowadays using new digital technologies in an increasing number of jobs and even those who do not use them are seeing the nature of their jobs changing as tasks are increasingly automated by digital processes and by AI-powered technologies. Many of the technologies used today did not exist 10 to 15 years ago. Even from an anecdotal point of view, it is clear that the speed by which digital technologies have permeated labour markets and societies has been extraordinary.

This chapter aims at quantitatively assessing the pace by which the demand for key digital skills in different areas has been spreading across labour markets over time. It does so by leveraging the information contained in online job postings and building indicators that measure the extent by which the demand for digital technologies has been permeating the various different parts of the labour market over time in order to provide insights on current as well as potential future trends.

6.1. Using online job postings to assess the speed by which key digital technologies are permeating labour markets

When using job postings to examine the diffusion of digital skills and technologies across labour markets, several previous studies have focused on counting the increase in the frequency with which the terms related to digital technologies have been mentioned across job postings.

Metrics based on the simple count of the frequency of digital skill mentions are, however, likely to miss whether such increase has been concentrated in a small number of sectors/occupations or if, instead, digital technologies and skill demands have actually spread across a wide variety of sectors and occupations, truly permeating labour markets. This latter question is arguably very important, as widespread diffusion of digital technologies across sectors and different job roles is what drive significant changes in the overall labour market that policy makers and firms need to adjust to.

In order to accurately capture the growth in the diffusion of skill demands in the digital economy across different sectors and occupations of the labour market, this chapter uses machine learning techniques applied to the analysis of online job postings to examine how much digital skills are interconnected with other skills across job vacancies and in employers' recruitment requirements.[2]

More “interconnected” skills tend to co-occur in a wide variety of different work contexts and are being used and demanded widely in the labour market in different job roles. To give an example, the ability to operate MS Excel is becoming increasingly important “*across*” a variety of different jobs as this specific skill becomes more interconnected in a wide range of jobs and it is used in a variety of tasks. To put it differently, the frequency with which the basic knowledge of digital spreadsheets (for instance MS Excel) is required by employers has not only increased in its absolute frequency (i.e. the number of times it is mentioned) but it is also, and perhaps more importantly, required in a wider range of different jobs from the service sector (i.e. to handle requests from customers) to manufacturing (i.e. to analyse shipping of products) up to the health care sector (i.e. to keep track of patients’ records). This suggests that this particular skill demand is permeating the labour market and that its diffusion has increased over time.

The following sections focus on the diffusion of 5 digital skills categories (and of the disaggregated skills therein):

1. Advanced data analytics,
2. Programming skills,
3. Cybersecurity skills,
4. Automation and internet of things,
5. Business and Sales Digital skills.

The aim of the chapter is to assess the speed by which the demand for these skills has been diffusing within the labour markets covered in this report.

The remainder of this chapter presents results for Anglophone countries for which longer time series are available starting in 2012 and where the time dynamics are more visible. Results for EU countries, instead, can be calculated for a relatively shorter time span in between 2018 and 2021, a period where labour markets have also been heavily affected by the impact of the COVID-19 pandemic. Due to some of these limitations results, for the EU countries should be considered with some caution and are discussed in a separate section at the end of the chapter.

Box 6.1. The digital skills diffusion index: Using machine learning to assess how fast digital skills are permeating the labour market

The text contained in online vacancies can be fed to NLP algorithms that transform the semantic information contained therein into mathematical vectors that can be understood and analysed by a machine (see Annex 6.A). Those mathematical vectors (which are meant to retain the meaning of the words they represent) occupy a specific place in a mathematical high-dimensional space, this latter commonly referred to as a "graph".

It is then possible to assess when vectors in a graph are connected with each other (when keywords co-occur in a specific job vacancy) or disconnected (when they never co-occur in the same vacancy). In graph theory, the "eigenvector centrality" and the "local clustering coefficient" are two measures that are commonly used to assess the influence of a node in a network or, in other words, to measure the degree and quality of connections of a keyword with the rest of words in the text under exam.

Originally, these measures were developed by researchers in Google and used in the PageRank algorithm to quantify the importance of the connections among web pages based on the textual/semantic information contained in it. The same measures can, however, be used to capture the number of connections that a skill keyword has with other skills as well as the "quality" of those connections across job postings, where higher-quality connections are those with other skills that are also highly connected to the rest of the skills across job requirements. This paper uses the linear combination of the eigenvector centrality and the local clustering coefficient (see Annex 6.A) to measure how well-connected (i.e. pervasive) each skill is in the labour market in a specific point in time. This, in turn, allows to calculate the change in the extent of such connections over time (i.e. the "diffusion index"), and to unveil whether a certain skill has become more or less connected (i.e. more or less pervasive) during the period under exam. These measures are used to indicate whether skills are diffusing across jobs and at what speed.

6.2. Advanced data analysis skills

Every day, humanity generates an incredible two and a half quintillion bytes of data (Marr, 2018[1]). Google alone processes more than 20 petabytes of data every day, which includes around 3.5 billion search queries. These already astonishing figures are poised to increase in the future as more and more digital devices connect to the internet and produce/collect data.

Advanced data analysis skills are, not surprisingly, at the core of the development and adoption of a variety of different digital technologies that leverage the use of the available digital data. The ability to understand data, which often comes in the form of unstructured text (i.e. web searches) or images (i.e. photos or videos uploaded to streaming platforms), is becoming a key skill in high demand in current (and, very likely, in future) labour markets.

In this chapter, five specific skills have been selected and grouped under the umbrella of 'advanced data analysis' skills[3] and relate to a peculiar aspect of advanced data analysis:

1. Big data
2. Artificial intelligence
3. Machine learning
4. Data science
5. Data visualisation.

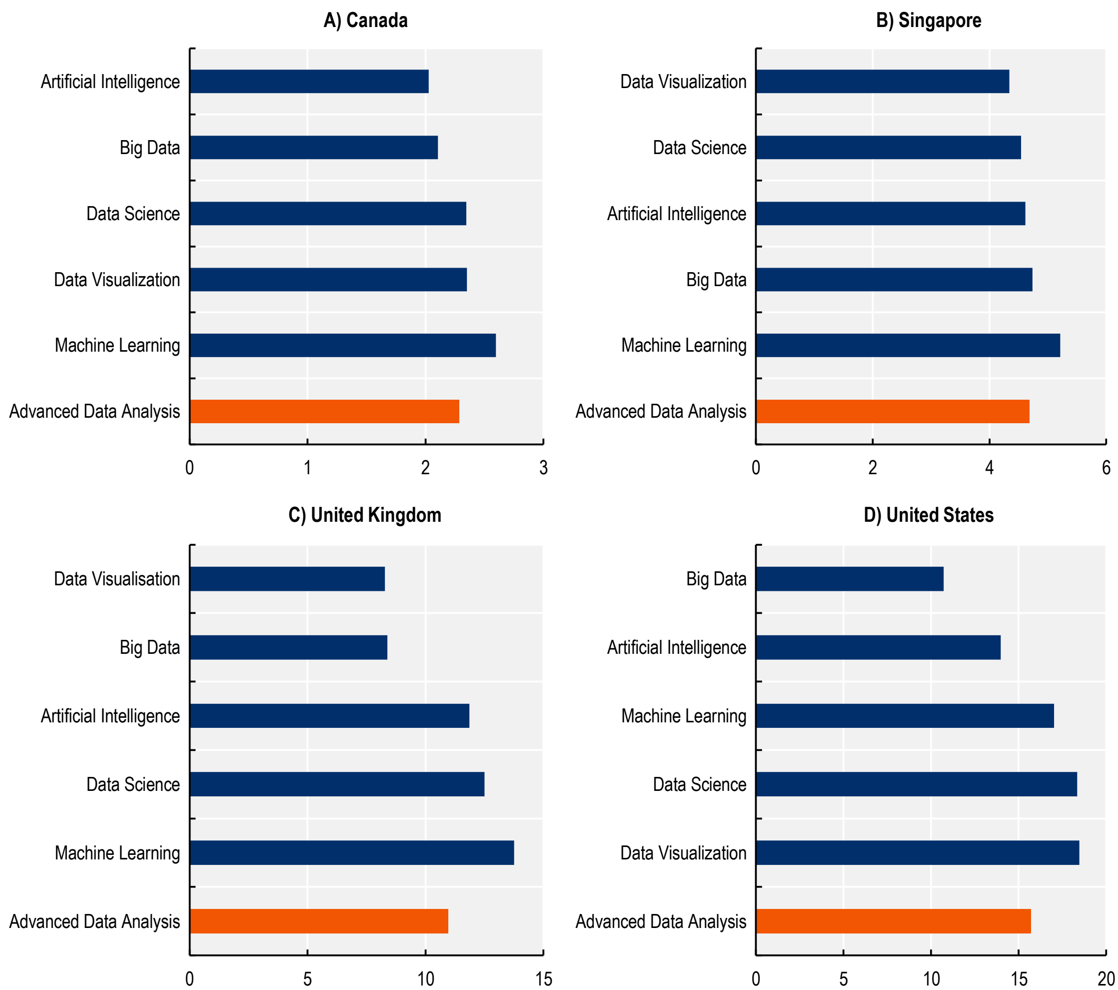
Big data skills, for instance, refer to the analytical techniques used to investigate very large and diverse big data sets that include structured, semi-structured and unstructured data from different sources, and in different sizes from terabytes to zettabytes. Machine learning refers to the use and development of computer systems that are able to learn and adapt their analyses without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data. Similarly, data science uses scientific methods, processes, algorithms and systems to extract knowledge and insights from noisy, structured and unstructured data. Data science is also at the core of the development of artificial intelligence, that is the ability of using new algorithmic techniques to analyse data and produce outputs that mimic human intelligence. Finally, data visualisation is an interdisciplinary field that deals with the graphic representation of data, essential to analyse massive amounts of information and make data-driven decisions based on them.

Evidence presented in Figure 6.1 presents estimates of the speed by which, on average, advance data analysis skills have been permeating labour markets over time. Results indicate that the demand for advanced data analysis skills has been growing considerably faster than the average skills across the labour markets examined in between 2012 and 2021. In Canada, for instance, results show that the demand for advance data analysis skills has been diffusing across jobs published online twice as fast as the demand for the average skill in the same economy. Results indicate that advance data analysis skills are not only mentioned much more frequently in online job postings than a decade ago, but also, that they are mentioned in a far wider range of jobs and work contexts, signalling that their use has spread from narrow contexts (for instance in the IT sector) to a much more varied set of sectors and jobs, from health care to finance for instance.

Results in Figure 6.1 shows significant heterogeneity across countries in the speed by which advanced data analysis skills have permeated labour markets. In Singapore, for instance, the speed with which the demand for advanced data analysis skills has been diffusing across occupations is almost five times that of the average skill.[4] Results are larger in the United Kingdom where the demand for advanced data analysis skills has spread 10 times faster than the demand for the average skill and in the United States, a country usually at the forefront of the technology adoption, where advanced data analysis skill demands have diffused more than 15 times faster than the average skill in its labour market between 2012 and the end of 2021. All in all, the analysis of job postings published online between 2012 and 2021 confirms that data analysis skills have become key in a variety of jobs and sectors. These trends are likely to continue in the future, fuelled by the increasing availability of datasets of different sorts, from text to images up to data recorded and collected by interconnected devices and appliances driven by the internet of things.

Figure 6.1. The speed of diffusion of advanced data analysis skill demands

Anglophone countries, 2012-21



Note: Values on the horizontal axis represent the speed by which the examined skill has been diffusing in the overall labour market (captured by online job postings) relative to the average skill. A value of 5, for instance, means that the examined skill has been diffusing 5 times faster than the average. The speed of diffusion is calculated using the eigenvector centrality and local clustering coefficient measures as detailed in Annex 6.A. Skills are ordered by the increasing speed of diffusion. Advanced Data Analysis is the average of the other skills listed in the figure.
Source: OECD calculations based on Lightcast data on online job postings.

Among the skills sub-components belonging to the group of advanced data analysis skills, Figure 6.1 reveals that machine learning has been growing the fastest over the period 2012 to 2021 across the countries analysed with the exception of the United States (where the demand for data visualisation and data science skills have been spreading at an even faster pace). Machine learning applications, particularly suited to analyse big data sets, are hence expected to grow at a fast pace, triggering a more widespread use of AI in different areas from health care to services and entertainment (see Box 6.1). As data become integral part of business decisions, also the visualisation of results based on big data will become increasingly important, spurring the demand for professionals able to create intuitive representations of complex systems. This is also reflected in the results in Figure 6.1.

Box 6.2. Artificial intelligence and machine learning in today's world and labour market

The seminal work by Alan Turing (Turing, 1950[2]) was the first academic contribution to pose the question "Can machines think?" and to suggest the idea that machines could perform cognitive task, replicating the behaviour of humans, in such an accurate way that machines would be eventually indistinguishable from their creators. Since then, a number of different definitions have been provided for the concept of "Artificial Intelligence" (AI henceforth).

The OECD AI's Experts Group (AIGO) (OECD, 2019[3]) defines an AI system as "*a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner* e.g. *with machine learning (ML) or manually); and use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy*".

In recent years, a lively debate has emerged as to whether AI should be treated differently from "traditional" automation technologies that perform narrow routine tasks (Autor, Levy and Murnane, 2003[4]). (Muro, Whiton and Maxim, 2019[5]) argue for instance that AI, differently from more traditional automation technologies, is making significant progress in replicating a particular aspect of intelligence, namely "prediction", this latter being central to decision making and an essential aspect of high-skilled jobs in the health care or business sector. Similarly, (Felten, Raj and Seamans, 2019[6]) and (Webb, 2019[7]), stressed AI's ability to perform non-routine cognitive tasks through their ability to autonomously "acquire" and "apply" knowledge in problem solving contexts.

New examples, showing the ability of AI to perform such tasks, are being developed at a fast pace. GPT-3 is, for instance, one of the most sophisticated AI-powered Natural Language Processing (NLP) algorithm to this date. The current version of GPT-3 is able to answer complex medical questions and to correctly identify a disease from the simple description of its underlying symptoms, even suggesting the necessary treatment for the disease at hand. Notably, GPT-3 capabilities are transversal, ranging from its ability to write new software code to that of programming mobile applications or to autonomously produce poems and journal articles when prompted with a few lines of text.

It is clear that the increasing ability of machines to perform cognitive tasks as effectively as humans is poised to have an enormous impact on the way services are delivered, products are manufactured and innovation itself is created. In short, AI is expected to revolutionise the way people interact with machines for leisure and at work in ways that are, however, still difficult to predict.

The fast-paced adoption of AI-powered technologies will certainly have fundamental repercussions on the type of skills that individuals will need to master in at least two separate ways. On the one hand, individuals will need to develop adequate digital and cognitive skills to interact with AI. AI, in fact, does not operate in a vacuum and much of its potential is determined by how well humans are able to interact with it by supplying the correct inputs and understanding the outputs that are produced in return. Similarly, individuals will need to be educated on how to detect biases, fakes and mistakes that could result from the misuse of AI.

6.3. Programming skills

Among the digital skills that are on the rise in labour markets' demands, programming skills occupy a key role as they are fundamental requirements for a variety of jobs that have been growing significantly in the last decade and that are expected to grow even further in the coming years (see Chapter 4). "Programming skills", as defined in this chapter, encompass a variety of different aspects related to the creation, management and use of software code. Among the skills grouped under this label there are programming principles (i.e. the basic principles, concepts and methods, for how a computation or algorithm is expressed), software development principles (i.e. the set of recommendations that engineers should follow during programme implementation to write clear and maintainable code), software development methodologies (i.e. the processes used in software development that define the strategies and phases used to organise and write the software code, encompassing different approaches such as Agile, Waterfall or Lean), and scripting languages skills (i.e. the knowledge of specific computer languages that can be used to give instructions to other software, such as a web browser, server, or standalone applications as many of today's most popular coding languages are scripting languages, such as JavaScript, PHP, Ruby, Python, and several others).

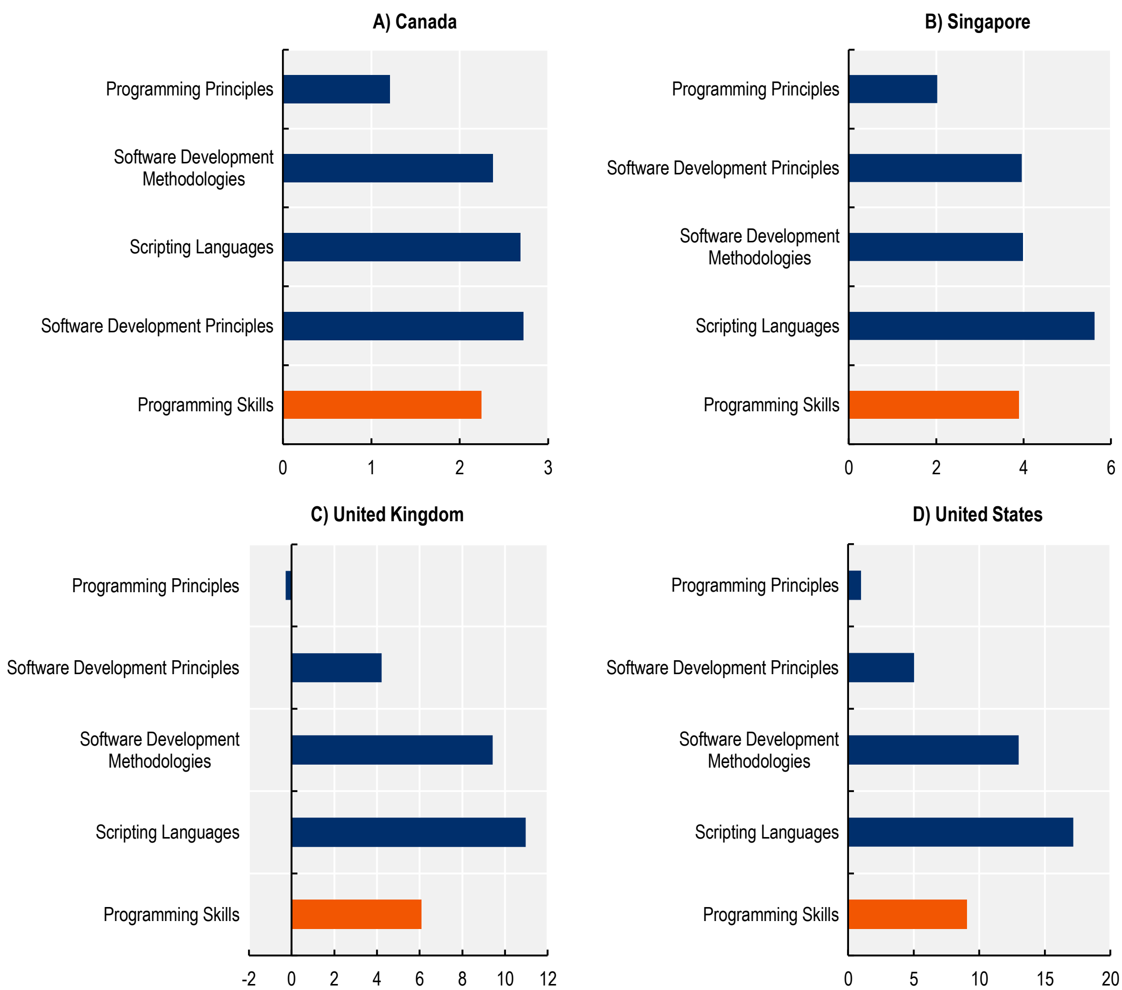
Results in Figure 6.2 indicate that the demand for programming skills has been diffusing at a very significant pace across all labour markets analysed. The speed of diffusion, however, varies across countries. The demand for programming skills has been diffusing in the United States and the United Kingdom at a particularly rapid pace (in between 6 and 9 times faster than the average skill) while the diffusion in other countries such as Canada and Singapore has been relatively slower, tough strong.

When looking at the skill sub-components in Figure 6.2, the demand for scripting languages skills, that is the ability to produce code in different programming languages such as JavaScript or Python, has been diffusing significantly faster than the average across all labour markets. In the United States, for instance, the demand for scripting languages skills has permeated the labour market at a pace that is up to 17 times faster than the one for the average skill. To put it in other words, results suggest that the firms and employers in the United States across a wide variety of sectors have been seeking workers able to operate Python, Ruby and many other scripting languages and that such increase in demand has spread across all sectors significantly faster than the average. Just taking the example of Python, this latter is nowadays used in a variety of different programming scenarios, from games to web applications which span across virtually all productive and service sectors.

Similar results, though to a lesser extent, can be found in the rest of the countries analysed, where scripting languages skills show up amongst the fastest diffusing programming skills. Interestingly, results also show that, while scripting languages skills have been diffusing very rapidly in labour markets, the demand for "simpler" programming principles (i.e. the basic principles of programming) have also diffused faster than the average skill, but at a much slower pace if compared with other programming skills. This seems to suggest that demand for more complex and technical programming skills (such as the ability to work with specific scripting languages) is increasing and diffusing at a faster pace than more basic programming skill demands and that, in the future higher-level digital skills are likely to be needed to fill forthcoming digital gaps.

Figure 6.2. The speed of diffusion of programming skill demands

Anglophone countries, 2012-21



Note: Values on the horizontal axis represent the speed by which the examined skill has been diffusing in the overall labour market (captured by online job postings) relative to the average skill. A value of 5, for instance, means that the examined skill has been diffusing 5 times faster than the average. The speed of diffusion is calculated using the eigenvector centrality and local clustering coefficient measures as detailed in Annex 6.A. Skills are ordered by the increasing speed of diffusion. Programming skills is the average of the other skills listed in the figure.
Source: OECD calculations based on Lightcast data on online job postings.

6.4. Automation and IoT

Digital technologies, the development and implementation of automation and of the internet of things (IoT) are tightly linked. Chapter 2 in this report discusses briefly the key role that automation and IoT are having on labour markets. The adoption of automation technologies across a variety of different sectors, from manufacturing to services, is contributing to the significant shift in skill demands observed in labour markets. Many workers today perform different tasks than a decade ago as they rely on automated machines to carry out the most repetitive operations while humans focus on more cognitive tasks. These changes are happening at a fast pace and spreading across a wide range of sectors, requiring workers to adapt to new technologies and interact with them in areas of the labour market that were unthinkable just a decade ago. Hotel check-in automation, for instance, allow today's tourists to access their rooms without having to interact with the hotel front desk, by simply showing a bar code. While this reduces the time spent by hotel staff to deal with receipts and documents' controls, it allows them to work on resolving other issues and emergencies when they happen. For instance, keeping guests' details in a digital form also means hotels can tailor their experience to them, including notes on possible allergies, preferences, or requests.

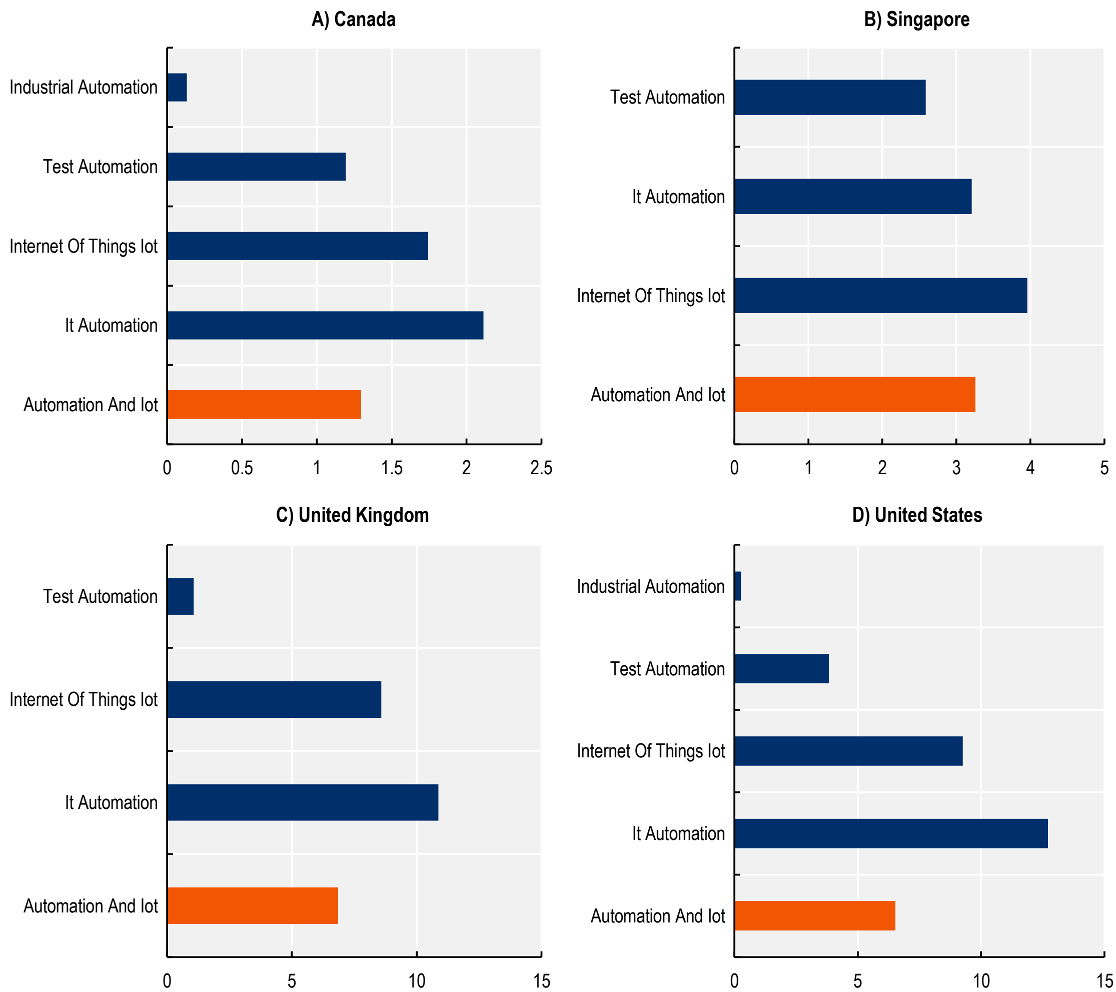
This type of automation is linked to the development of the so-called Internet of Things (IoT). IoT is best described as the technology underlying the connection of systems and devices (say the door of the hotel) to sensors, software, and other technologies that enable those devices to exchange data with other devices and systems over the Internet.

In the consumer market, IoT technology is synonymous with products for "smart homes" (i.e. interconnected lighting or heating systems) and "wearables" (i.e. smart watches). The IoT is, however, expanding rapidly to other areas such as "smart cities" (i.e. connecting cars to parking spaces, managing the efficient use of resources etc.). In the agriculture sector, John Deere (an American corporation that manufactures agricultural machinery, heavy equipment, forestry machinery), recently acquired Silicon Valley-based Blue River Technology to further the company's goal of applying IoT to their activities. IoT, in that context, is used to monitor moisture levels, air and soil temperature and wind speed and convey the collected data to farmers. The company's tractors and other types of equipment are outfitted with satellite-connected guidance and tracking systems that cull data allow for what's called "precision farming," which greatly increases the efficiency of fertilizers and pesticides.

Results in Figure 6.3 confirm the rapid diffusion of skill demands related to automation and IoT in the countries analysed. On average, automation and IoT skill demands diffused up to 6 times faster than other skill demands in labour markets, with a particularly fast pace in the United Kingdom and the United States. Despite their fast diffusion, when compared to other skill demands analysed above (advanced data analysis or programming skills), results seem to suggest that automation and IoT skill demands are still relatively concentrated in a narrower set of jobs. This is to say that, while automation has certainly spread across different sectors, the range of jobs that require a deep knowledge of automated systems or the implementation of new IoT systems seem to remain relatively smaller than in the case of other, more mainstream, digital-related skills.

Figure 6.3. The speed of diffusion of automation and IT skill demands

Anglophone countries, 2012-21



Note: Values on the horizontal axis represent the speed by which the examined skill has been diffusing in the overall labour market (captured by online job postings) relative to the average skill. A value of 5, for instance, means that the examined skill has been diffusing 5 times faster than the average. The speed of diffusion is calculated using the eigenvector centrality and local clustering coefficient measures as detailed in Annex 6.A. Skills are ordered by the increasing speed of diffusion. Automation and IoT is the average of the other skills listed in the figure.
Source: OECD calculations based on Lightcast data on online job postings.

6.5. Cybersecurity

In a world that is reliant on interconnected devices and where large amounts of sensitive data are stored to improve decision making, cyber threats and data breaches pose significant risks for governments and businesses. In order to reduce vulnerability to cyberattacks, organisations are increasingly investing in cybersecurity and IT risk management. Reducing organisational level vulnerability to cyber threats requires investments in a cybersecurity ecosystem that takes a proactive and not only reactive approach to the management of cyber threats. This involves training cybersecurity professionals, as well as develop organisation-wide cybersecurity risk managerial decision-making, and a broad workforce that operates in a way that reduces exposure to cyber-attacks.

The demand for workers with cybersecurity skills has been increasing significantly in recent years (see Chapter 4) and it is expected to grow even faster in the near future. Several commentators expect that this trend will continue in the future and create bottlenecks and shortages in labour markets, and is already doing so in several countries as geopolitical tensions increase as well as cyber-attacks.

The analysis of job postings shows that the demand for cybersecurity skills has diffused very rapidly within labour markets and across occupations. The knowledge of cybersecurity is required in different roles spanning from Information Security Analysts (in charge of planning implementing, upgrading, or monitoring security measures for the protection of computer networks and information) to Security Management Specialist and Network and Computer Systems Administrators (see Table 6.1).

Table 6.1. Examples of jobs where Cybersecurity skills are particularly relevant

United States, 2019

Top 5 occupations by Cybersecurity skill relevance	Number of new job postings per year
Cyber / Information Security Engineer / Analyst	145922
Security Management Specialist	15873
Security / Defense Intelligence Analyst	10783
Security Manager	12348
Network / Systems Administrator	87410

Source: OECD calculations based on Lightcast data on online job postings.

Across countries, results in Table 6.2 show that the demand for Cybersecurity skills has been diffusing at a fast pace in particular in the United Kingdom and in the United States (in between 6 to 10 times faster than the average skill in those countries respectively). The diffusion, despite being faster than the average, has been relatively slower, instead, in Singapore and Canada where cybersecurity skill demands have been increasing but remained requested with high relevance in a narrower set of jobs.

Table 6.2. Diffusion of cybersecurity skill demands

Time period: 2012-21

Country	Speed of diffusion of cybersecurity skill demands relative to average skill
Canada	1.8
Singapore	3.4
United Kingdom	6.6
United States	10.4

Source: OECD calculations based on Lightcast data on online job postings.

6.6. Business and sales digital skills

Digital technologies are nowadays used by businesses in virtually all productive sectors. Increasingly in the last decade, digital tools have been used to spur businesses' productivity by, for instance, by streamlining accounting operations and supporting sales through business intelligence or through the creation of social media business accounts reach out new and old customers.

In a recent Forbes' article (Higgings, 2021[8]), for instance, highlights how technologies such as cloud-based data management, process automation and advanced analytics are actually poised to elevate business accountants in new and empowering ways as new digital technologies will support rather than replace workers in those business positions. In the accounting work context, "*centralizing data management, particularly through the use of cloud technology, reduces waste and lowers costs considerably by improving communication and collaboration. Standardization and a cohesive datasphere make it easier to capture, access, share and analyze data. Transparency improves as data silos are dismantled, and data quality rises, rather than falls, with data quantity*". In a highly digitalised business, accountants can then put their uniquely human skills to transforming the insights extracted from high-quality data into more effective financial planning and reporting.

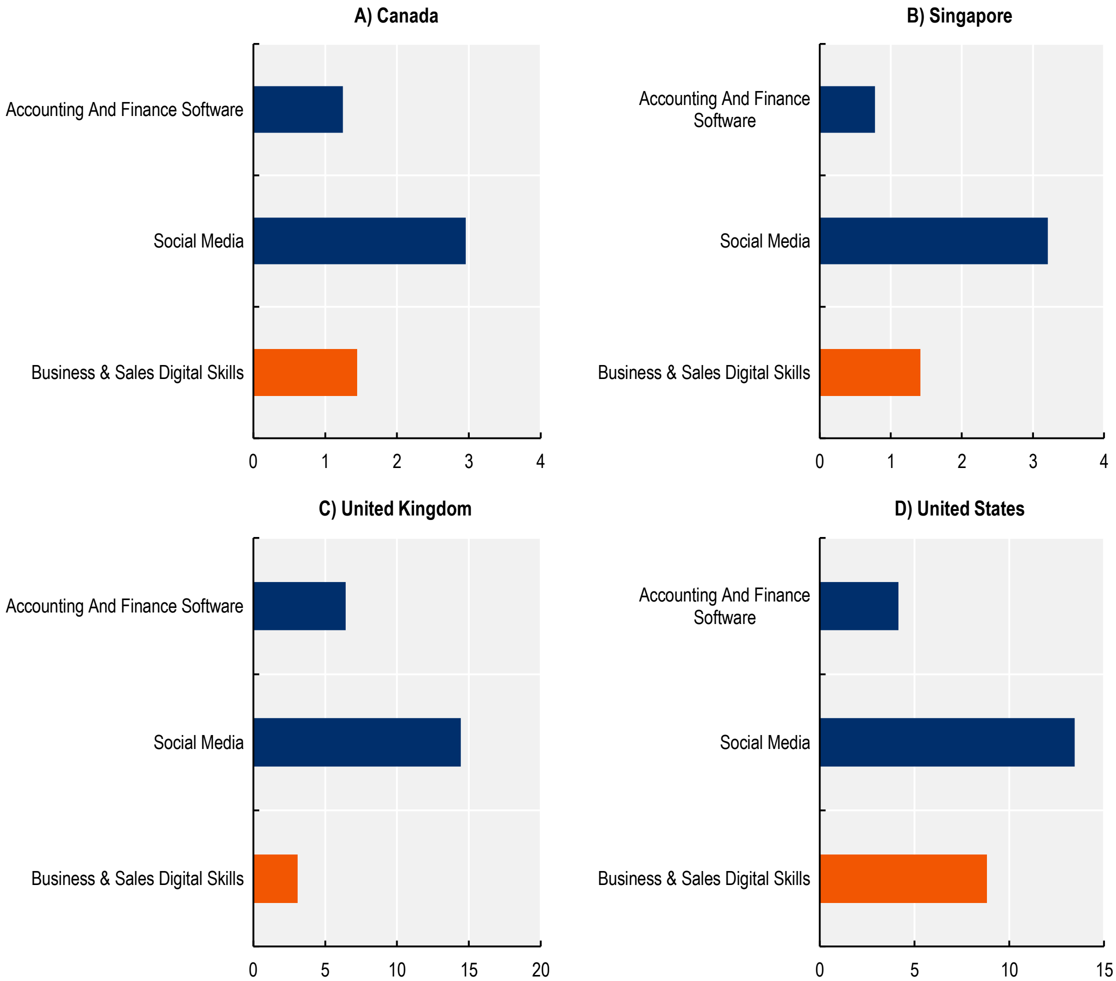
Results in Figure 6.4 show that the demand for business accounting digital tools has spread over time significantly faster than other skills. The demand for accounting and finance software related skills has diffused in between 4 to 6 times faster than the average skill in the United Kingdom and the United States. Similar pattern is observed for Canada and Singapore, though the diffusion of the demand for those skills has been relatively slower.

Along with accounting and finance digital tools, businesses have increasingly started using new sales strategies to reach their customers, many of which heavily rely on digital technologies. Among those, a key role is played by businesses' social media which, channelled through digital platforms and technologies, can significantly spur productivity and sales. (Pourkhani et al., 2019[9]) highlight how "*today social media platforms such as Twitter and Facebook enable the creation of virtual customer environments (VCEs) where online communities of interest form around specific firms, brands, or products*". Most large brands today (but also a quickly increasing share of small, medium as well as micro enterprises) have a Twitter, Facebook or Instagram account that they use to interact with customers, manage orders, shipping and requests as well as complaints. Social media are also used to gather information from customers. On Instagram, for instance, businesses can collect feedback from followers by posing questions or polls while other digital tools can also be used to monitor the sentiment of customers by looking for instance at the use of specific keywords (or hashtags) in social media posts.

Results in Figure 6.4 that the uptake of social media has been very fast in the period between 2012 and 2021. The demands for social media skills has diffused up to 3 times faster than the average skill in Canada and Singapore, while the diffusion has been stronger (up to 14 times faster) in the United Kingdom and in the United States, suggesting that a rapidly increasing number of businesses are now hiring (or searching for) workers with skills in the area of social media management.

Figure 6.4. The speed of diffusion of digital business accounting and social media skill demands

Anglophone countries, 2012-21



Note: Values on the horizontal axis represent the speed by which the examined skill has been diffusing in the overall labour market (captured by online job postings) relative to the average skill. A value of 5, for instance, means that the examined skill has been diffusing 5 times faster than the average. The speed of diffusion is calculated using the eigenvector centrality and local clustering coefficient measures as detailed in Annex 6.A. Skills are ordered by the increasing speed of diffusion. Business and Sales Digital skills is the average of the other skills listed in the figure.
Source: OECD calculations based on Lightcast data on online job postings.

6.7. The diffusion of digital skills in EU countries

Relative to the Anglophone countries analysed above, data on online job postings for EU countries are available for a shorter period of time in between 2018 and 2021. Such a shorter time series makes the detection of long-term trends in skill diffusion comparatively more difficult for EU countries. In addition, most of the time series for EU countries coincide with the period marked by the unprecedented COVID-19 crisis which, as pointed out in Chapter 4, has had important repercussions on labour markets across all countries. Despite these methodological challenges, the analysis of EU data still brings interesting elements to the understanding of the diffusion of digital skill demands across countries.

Table 6.3 shows the list of top 5 digital skills for each EU economy analysed in this report over the period 2018-21, ranked by the speed of diffusion of their demand across online job postings within each country.

Table 6.3. Top 5 digital skills by speed of diffusion across online job postings

Period: 2018-21

Belgium	Germany	Spain	France	Italy	Netherlands
Ubuntu	Javascript	Ajax	Ubuntu	CSS	Ubuntu
AngularJs	AngularJs	Google Analytics	Salesforce	Ubuntu	SAP
SAP	SAP	C+	Computer Science	Excel	AngularJs
Digital Marketing Techniques	Software Design Methodologies	Use Software Design Patterns	CSS	SAP	Javascript
Information And Digital Content	Web Services	SQL Server	Javascript	Unified Modelling Language	Unified Modelling Language

Note: The speed of skill diffusion is calculated using the eigenvector centrality and local clustering coefficient measures as in Annex 6.A.
Source: OECD results based on Lightcast data for EU countries.

The knowledge of how to operate Ubuntu, an open source Linux-based operating system designed for computers, smartphones, and network servers shows among the digital competencies that have diffused faster across EU countries, in particular in Belgium, France and the Netherlands in between 2018 and the end of 2021. In this context it is interesting to notice that Linux has gradually improved its market share in the last few years and that notable growth in its adoption (perhaps triggered by its open-source nature compared to alternatives with significant licencing costs) has been the strongest in 2020 which is also reflected in the speed by which Ubuntu has been diffusing in job requirements across labour markets.

The demand for Javascript skills (a programming language that is one of the core technologies of the World Wide Web) has also been diffusing particularly rapidly across EU countries. As highlighted in Chapter 5 of this report, Java is particularly relevant for software developers and programmers but those skills have been diffused rapidly also in other fast growing digital roles such as computer systems engineers and web developers and UI / UX designers / developers. This is reflected in the results in Table 6.3 where Javascript skills are amongst the digital skills that have diffused faster in Germany, the Netherlands and France. Javascript skills are also related to other technical skills that have been diffusing very fast across the demands of employers in online job postings such as the knowledge of Ajax (a set of web development techniques that uses various web technologies to create web applications), Cascading Style Sheets (CSS, a cornerstone technology of the World Wide Web, alongside HTML and JavaScript) or AngularJs (AngularJS is a toolset for building the framework most suited to application development) which have diffused at a rapid pace in all EU countries analysed.

Results in Table 6.3 also show that several business-related digital skills have been on the rise in EU countries' demands from employers. The demand for SAP (Systems, Applications and Products in Data Processing) related skills has been on the rise, particularly in Belgium, Germany and Italy, but generally digital competences related to digital marketing as well as Google Analytics and Sales Force have been permeating labour markets much at a fast pace, signalling the adoption by firms of digital tools used to manage their customer and enterprise relationship management.

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Annex 6.A. Leveraging big data to assess the diffusion of digital skill demands in labour markets

The vector representation of skill keywords in a n-dimensional space is also functional to assess the connections across skills and, as such, the degree by which skills are pervasive in the observed labour market published online. The connections between a group of keywords can be represented by a so-called skill graph. In such graph, the keywords extracted from online vacancies represent the vertices (also called nodes) which can be either connected when both vertices co-occur in a specific job vacancy, or disconnected when both vertices never co-occur in the same vacancy.

A so-called adjacency matrix can be built to represent these skill co-occurrences.[5] Whenever a skill co-occurs with another skill in a certain job vacancy, the row corresponding to the skill "A", and the column corresponding to the skill "B" will get the value 1. Note that the adjacency matrix is symmetric, meaning that the co-occurrence between skills is undirected and therefore commutative.

One can hence use this adjacency matrix to calculate the eigenvector centrality (EVC) and the local clustering coefficient (LCC) for each skill. The power iteration algorithm is used to derive the relativity score for each vertex v in the network. Given a graph G, and adjacency matrix A, the relative centrality score of a certain skill can be defined as:

$$EVC_v = \frac{1}{\lambda}\sum_{t\in M(v)} \quad EVC_t = \frac{1}{\lambda}\sum_{t\in G} \quad a_{v,t}EVC\lambda$$

Since this is an undirected graph, the local clustering coefficient can also be defined as:

$$LCC_i = \frac{e_{jk}: v_j, v_k \in N_i, e_{jk} \in E}{k_i(k_i - 1)}$$

Both measures serve as an important indicator for contextual diversity and the importance of certain skills as compared to other skills in the network. In graph theory, the "eigenvector centrality" and the "local clustering coefficient" are two measures that are commonly used to assess the influence of a node in a network or, in other words, to measure the degree and quality of connections of a keyword with the rest of words in the text under exam. Originally, these measures were developed by researchers in Google and used in the PageRank algorithm to quantify the importance of the connections among web pages based on the textual information contained in it. The same measures can, however, be used to capture the number of connections that a skill keyword has with other skills as well as the "quality" of those connections, where higher quality connections are those with other skills that are also highly connected to the rest of the skills in the vector space.

One can finally create a unidimensional measure of skill diffusion by normalizing and rescaling the eigenvector centrality and the local clustering coefficient into a single measure using the following:

$$Diffusion_{it} = \frac{EVC_{it} + (1 - LCC_{it})}{2},$$

The change over time of the Diffusion index is used in the analysis above to measure the degree by which skills have become pervasive in the labour market. The Diffusion index is computed for each skill keyword analysed in the database of online job postings and compared to the average diffusion across all skills in each economy where faster diffusion of a skill means an increase (above average) of the connections of that particular skill with other skill demands across job postings, hence an increase in how much that skill is permeating the labour market in a variety of different work contexts and job roles.

Notes

[1] Adaptive bitrate streaming technology a method of video streaming over HTTP where the source content is encoded at multiple bit rates.

[2] In particular, the analysis in this chapter applies the concept of eigenvector centrality and local clustering coefficients to the analysis of the information in online job postings. Both eigenvector centrality and local clustering coefficients have been used by companies like Google to assess connections between webpages and to identify networks and relationships between them.

[3] The selection of skill keywords falling in each broader skill category has been done in consultation with experts from Randstad Research Italy, whose support is greatly appreciated. Indeed, more skill keywords could have added to the selected list, which is not meant to be exhaustive but representative of different aspects related to advanced data analysis.

[4] As labour markets evolve rapidly, so do also skill demands. Each skill analysed in the database of online job postings may increase its diffusion (if it is mentioned in a wider variety of jobs) or decrease it (if it is mentioned in a narrower set of jobs). Notice that the measure of speed of diffusion for digital skills is computed relative to the average diffusion of skills across the labour market.

[5] The extracted skill graph forms an undirected acyclic graph, meaning that skills do not co-occur with themselves. As a result the diagonal of the adjacency matrix is 0.

7 Retraining pathways and transitions from declining to thriving occupations

This chapter discusses how to use big data and the information contained in millions of job postings collected from the internet to design retraining pathways for workers employed in occupations in decline who are willing to move into occupations in high demand. Retraining pathways are built by comparing the skill demands across different sets of occupations and leveraging the granular information contained in job postings. This approach allows to identify detailed lists of skills that workers willing to switch career would need to develop in order to reach the competency level required to perform in occupations in high demand. The chapter presents three example of such retraining pathways, describing how such an approach could be extended to a wider range of occupations in order to strengthen labour market matching and retraining programmes.

The adoption of digital technologies requires the workforce to integrate them in the production processes in which businesses operate. Firms and workers, in turn, need to adapt to the new skill needs that the labour market may demand as a result of the adoption of digital technologies. Over the past few years, this type of changes have been very tangible: new jobs (mainly in the digital sphere) have been created, others have disappeared (or risk doing so in the near future) and, overall, the skills required to undertake most occupations have changed significantly, largely as a result of the digital revolution.

Reflective of this is the World Economic Forum's recent report (World Economic Forum, 2020[1]), which estimates that 85 million jobs may be displaced by 2025 as a consequence of the shift in the division of labour between human labour and machines. Similarly, however, around 97 million jobs may be created as a result of the digital transition.

While the overall impact of digitalisation on employment is still the subject of a lively debate, it is becoming increasingly clear that the gains from the transition to a digitalised world are unlikely to be shared evenly among workers (OECD, 2019[2]). Certain groups of individuals, in particular the low-skilled workers and those with low education attainment levels will have to adjust to new skill demands (see Box 7.1).

Box 7.1. Low-skilled and the digital divide: The need for inclusive policies

Technological progress has the potential to improve the well-being of individuals by increasing productivity and economic growth. Similarly, technological progress can potentially deepen income, gender, age and territorial inequalities if only a subset of individuals is capable of reaping the benefits of new (digital) technologies. Low skilled workers, for instance, have become substantially concentrated in occupations at high risk of automation. Just to give an example, in between 2012 and 2019 (the pre-pandemic year), the average share of low-educated workers in the six riskiest occupations increased by 5.9%. Lifelong learning, training and upskilling of low-skilled individuals play a key role in countries' ability to make the digital transition inclusive and work for all. Recent work (OECD, 2021[3]) highlights the importance of promoting interest in adult learning as a key tool for low-skilled workers to benefit from the gains stemming from digitalisation. To turn this into reality, governments need to act to boost incentives for low-skilled workers to participate in training by, among others, reducing financial and time barriers to participation in lifelong learning, while promoting training offer that is better aligned to the needs of the labour market.

In today's rapidly-changing labour market, one key challenge lies in ensuring that workers are able to move from declining occupations to the others that are expected to thrive as labour market demands changes (OECD, 2021[3]). To ensure that these transitions are effective, workers in declining occupations should be able to upskill and retrain to move to roles that are in high demand in labour markets. But what are the specific skills that are needed to effectively transit from a declining occupation to a thriving one?

To investigate these career moves, this chapter starts by describing the concept of "occupation clusters" by identifying sets of occupations that share similar skill requirements and among which career transitions are likely to be relatively easy due to the overlap in their skill demands. To illustrate the idea of occupation clusters, one occupation of reference is placed in the centre of the occupation cluster where other (similar) occupations are found around it at a certain distance. The distance between the centre of the cluster and the rest of occupations represents the similarity between occupations' skill requirements (see Box 7.2).

Box 7.2. The concept of occupation clusters

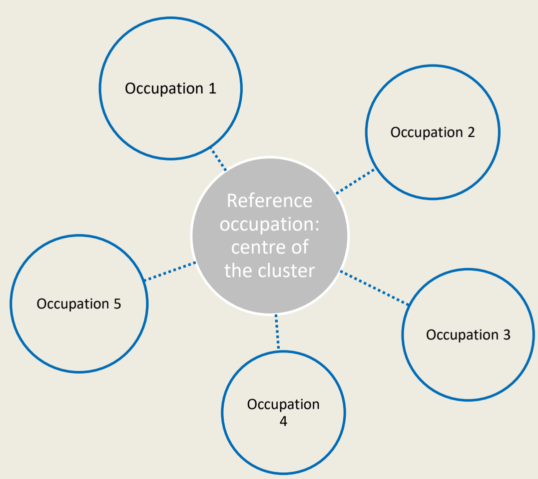
The concept of occupation clusters is used here to depict the similarity between a reference occupation and other occupations that are related to it, having similar skill requirements. In the remainder of the analysis, this chapter will build occupation clusters by identifying the occupations that are most similar in terms of skill requirements to the one at the centre of each cluster (the reference occupation). The farther away an occupation is from the centre and the more dissimilar its skill requirements are relative to the reference occupation.

A measure of "occupation similarity" (i.e. the distance between the centre of the cluster and other occupations close to it) is built based on the analysis of the skill demands contained in online job postings which leverages natural language processing algorithms to assess the overlap between skill requirements across occupations. For instance, customer service managers (one of the occupation under exam in the analysis that follows in this chapter) are "close" to call centre managers or sales supervisors as those jobs require similar skills.

Being slightly more technical, the measure of occupational similarity is computed as the cosine similarity between the vector representing each occupations which are obtained applying the Doc2Vec natural language processing algorithm to the information contained in online job postings. The algorithm produces a mathematical vector representing each occupation in terms of the relevance of its underlying skill requirements as they appear in the demand of employers who publish job adverts online. Mathematical vectors distant from each other signify that underlying occupations share few or no skill requirements with each other. Conversely, occupations that share a high degree of skill similarity will be represented in vectors that are close to each other in the vector space and where their cosine similarity is high.

It is worth noting that, by definition, occupations within each cluster share similar skill requirements and are natural candidates for career moves within it. Customer service managers, for instance, could easily retrain to become call centre managers as that occupation belongs to the same cluster and share similar skills. While some transitions may be easy from a retraining point of view, this chapter focuses on those transitions between occupations that are declining in terms of employment and those whose demand is expected to increase and that are "digital" in nature.

Figure 7.1. Example of an occupation cluster



Note: Each bubble represents an occupation. The one in the centre is the reference occupation of the cluster while those around it are occupations that are similar to it in terms of skill requirements. The closer an occupation is to the centre and the higher the degree of similarity of its skill requirements to the reference occupation. The measure of occupational similarity is built using the cosine similarity of occupation vectors computed using natural language processing algorithms (Doc2Vec) that pool together all skill requirements mentioned for any given occupation across online job postings for the country under exam.

In the remainder of this chapter, the analysis focuses on different pairs of origin-to-destination occupations by first identifying occupations whose employment is projected to decline that will be used as the "origin" occupations and "destination" occupations (whose employment outlook is particularly bright and expected to grow in the future).[1]

The pairs of origin-destination occupations that are used to illustrate a selection of results have been identified in such a way that the retraining effort that will be needed to move from a declining (origin) occupation to a thriving (destination) occupations is the lowest. This is to ensure that the transition is reasonable in terms of the skill acquisition that would be required to move from one to the other.

Given the scope of this report, the destination occupations are also selected to be "digital" in nature such that, the destination clusters will contain several of the "digital jobs" that have been analysed in previous chapters of this report. By no means, however, the analysed transitions constitute the only career transitions that are possible. They are, instead, examples in this chapter that has to be interpreted as a case study. Finally, to illustrate the results, this chapter focuses on the United States for which granular data on employment projections can be merged with the information contained in online job postings.[2] Table 7.1 presents the pairs of occupations that will be analysed in this chapter and that represent the centre of each occupation cluster described in the text below.

Table 7.1. Transitions from declining occupations into growing digital occupations in the United States

		Projected employment growth (2020-30)	Occupation similarity index
Group 1			
Origin occupation	Advertising sales agents /Account executive	-18.7%	0.46
Destination occupation	Digital Marketing specialist	22.1%	
Group 2			
Origin occupation	Satellite / broadband technician	-1.1%	0.32
Destination occupation	Computer support specialist	8.9%	
Group 3			
Origin occupation	Customer service manager	-1.5%	0.29
Destination occupation	Data engineer	7.8%	

Note: The occupational similarity index is calculated as the cosine similarity between the document vector representing the origin occupation and the document vector representing the destination occupation using the Doc2VEC NLP algorithm. On the cosine similarity measures see (Annex 3.A of this report). Higher values of the occupation similarity index represent occupations with more similar skill requirements, that is those with a larger cosine similarity (see Box 7.2). The index varies in between 0 and 1. Projected employment growth is based on the US Bureau of Labor Statistics projections (US Bureau of Labor Statistics, 2021[4]) see also Box 7.3. The taxonomy of the Lightcast database is expressed in SOC 2010 terms (at the sixth-digit level, although expanded to the eight-digit level by Lightcast), whereas the projections refer to SOC 2018. A cross-walk between the two versions occupational taxonomies has been used.
Source: OECD calculations based on Lightcast data and US Bureau of Labor Statistics projections.

Box 7.3. United States' employment projections by occupation

The projections presented in this chapter draw from the US National Employment Matrix database produced by the Bureau of Labor and Statistics (BLS). The matrix displays data on base- and projected-year employment and employment change. BLS produces occupational employment projections by analysing current and projected future staffing patterns (the distribution of occupations within an industry) in an industry-occupation matrix. Changes in the staffing pattern for each industry are projected and applied to the final industry projections, yielding detailed occupational projections by industry. This projected employment matrix includes estimates for 790 occupations across 295 industries. The Occupational Projections Data database displays data on employment, employment change, occupational openings, education, training, and wages for each detailed National Employment Matrix occupation.

7.1. Advertising sales agents/account executives vs digital marketing specialists: Occupational clusters and retraining pathways

7.1.1. Occupation clusters for account executives and marketing specialists

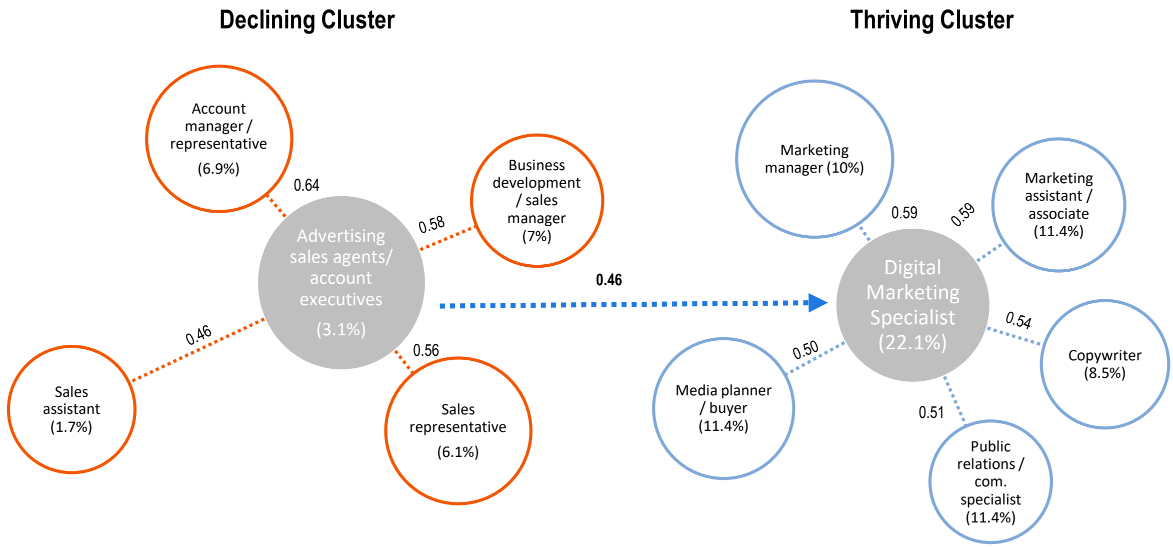
The advent of automation and the digitalisation of many routine tasks is affecting a variety of sales and accounting occupations. The role of traditional advertising sales or that of account executives, for instance, are changing rapidly as new automation technologies are replacing workers in a variety of routine tasks. Salesforce management systems, for instance, are nowadays used in customer relationship management marketing, helping to automate sales and sales force management functions. They are often combined with a marketing information system in CRM (Customer Relationship Management) systems.

Similarly, the Bureau of Labor Statistics (BLS) in the United States underlines that while "*advertising will continue to grow in digital media, including online video ads, search engine ads, and other digital ads intended for cell phones or tablet-style computers […] the ability to automate digital ad placement and the use of ad blockers by digital users will limit employment demand for advertising sales agents along these channels*" (US Bureau of Labor Statistics, 2021[4]).

The digitalisation of services is also affecting the demand for workers in some sales and executive roles indirectly. For instance, the US BLS also point out that "*the decline of print advertising will drive an overall employment decrease for advertising sales agents. Both newspapers and magazines have seen circulation declines that are expected to continue. With fewer consumers viewing advertisements in print media, fewer advertising sales agents will be needed to support ads in these media"* (US Bureau of Labor Statistics, 2021[4]).

As a reflection of these technological innovations and industry shifts, the BLS projections indicates that the growth in employment for advertising sales agents/account executive (SOC 41-3011) is expected to be significantly lower than the average growth in the United States (approximately 3% by 2030), where most of the new jobs that will open in the future will aim to replace workers who transfer to other occupations or those that retire.

Figure 7.2. Occupation clusters: Executive secretaries/executive administrative assistants and digital marketing specialists



Note: The figure shows the two occupation clusters for i) advertising sales agents/account executives on the left and ii) digital marketing specialists on the right. The most similar occupations to the one shown in the centre of each cluster are identified by a dashed line above which the occupational similarity index is placed. Higher values of the occupational similarity indicate a higher degree of skill overlap between origin and destination. BLS employment projections for the period 2020-30 are indicated in brackets within each bubble/occupation. The blue line connects the two occupation clusters, highlighting potential career pathways from declining to thriving occupations.
Source: OECD calculations based on Lightcast data; and US Bureau of Labor Statistics (2021[4]).

If advertising sales agents and account executives are facing a rather gloomy labour market outlook due to technological change, similar occupations that share a high degree of skill overlap with them are also (perhaps not surprisingly) at high risk of decline in labour markets. This is explored in Figure 7.2 that identifies the jobs that are closest to advertising sales agents/account executives in terms of skill requirements and that belong to the advertising sales agents' occupation cluster (see Box 7.2 above).

The analysis of online job postings for the United States in 2019, for instance, shows that account manager representatives, business development/sales managers, sales representatives and sales assistants are amongst the occupations that share the highest degree of skill similarity with advertising sales agents and account executives. Account managers and representatives or sales agents, for example, perform a variety of tasks that are similar in nature to those performed by advertising sales agents/account executives. Among them there is the traditional knowledge of accounting as well as all tasks that are related to customer relationship management practices.

Notably, as in the case of advertising sales agents, Figure 7.2 shows that the employment of account manager or sales agents is expected to grow at a speed that is below the average in the United States, hinting to the fact that several of those job roles similar to advertising sales agents/account executives are facing an equally worrying risk of automation and of technological displacement.

While technological change is certainly among the main drivers of the expected displacement and decline in employment of the occupations mentioned above, digitalisation represents also an opportunity for many of those workers to develop new skills and transit to different career paths that are digital in nature and are expected to thrive in future labour markets.

The analysis of skill demands in online job postings (Figure 7.2, right panel) helps identifying a series of different career options that advertising sales agents could consider, should they desire to move into thriving digital-related occupations. The digital occupations in Figure 7.2 (right panel) are expected to grow significantly in employment in the future and they are also the closest (in terms of skill requirements) to advertising sales agents. Among those, digital marketing specialists share the highest degree of skill similarity relative to advertising sales agents and are a plausible career switch option.

It is interesting to notice that marketing specialists are a clear example of an occupation that has experienced a significant transformation with the advent of digitalisation and that is nowadays leveraging digital technologies massively from web analytics to online marketing, through the knowledge of sophisticated software such as SemRush or Pardot.

Figure 7.2 ranks the ten most relevant skills for digital marketing specialists by the intensity of the retraining and upskilling that advertisement sales agents would need to undertake to move to that occupation.

Table 7.2. Retraining pathways: Acquiring the necessary skills, competences and knowledge in technologies to move from advertising sales agents to digital marketing specialists

Skill distance between origin and destination occupations, selection of the 10 most relevant skills at the destination occupation in the United States

	Skill distance from **origin** to **destination**
Web Analytics	0.246
Online Marketing	0.202
Semrush	0.200
Online Sales	0.168
SEO Copywriting	0.161
Brand Management	0.158
Advertising	0.132
Marketing Management	0.130
Online Advertising	0.057
Pardot	0.054

Note: The skill distance between the origin and destination occupation is computed as the difference between the skill relevance of each skill between the two occupations. Skill relevance scores are derived applying natural language processing algorithms to the information contained in OJPs as detailed in Annex 3.A in this report.
Source: OECD calculations based on Lightcast data for the United States in 2019.

Results show that advertisement sales agents would need to boost their knowledge, in particular, on web analytics and online marketing where the distance between the typical tasks they perform in their current jobs and those of digital marketing specialist is the largest.

Similarly, given the digital nature of marketing specialists' job, retraining or upskilling in the use of SemRush (a SaaS platform that is used for keyword research and to produce online metrics such as search volume and cost per click) will be also typically needed to access the job. Knowledge of online sales (rather than traditional sales) and of SEO Copyright are also key for advertising sales agents to move into digital marketing specialists.

Along with digital marketing specialists, however, Figure 7.2 (right panel) also shows other connected careers pathways, going from marketing managers to copywriters to media planners, all of which share a high degree of skill similarity with marketing specialists and are also occupations projected to grow significantly in the next decade in the United States.

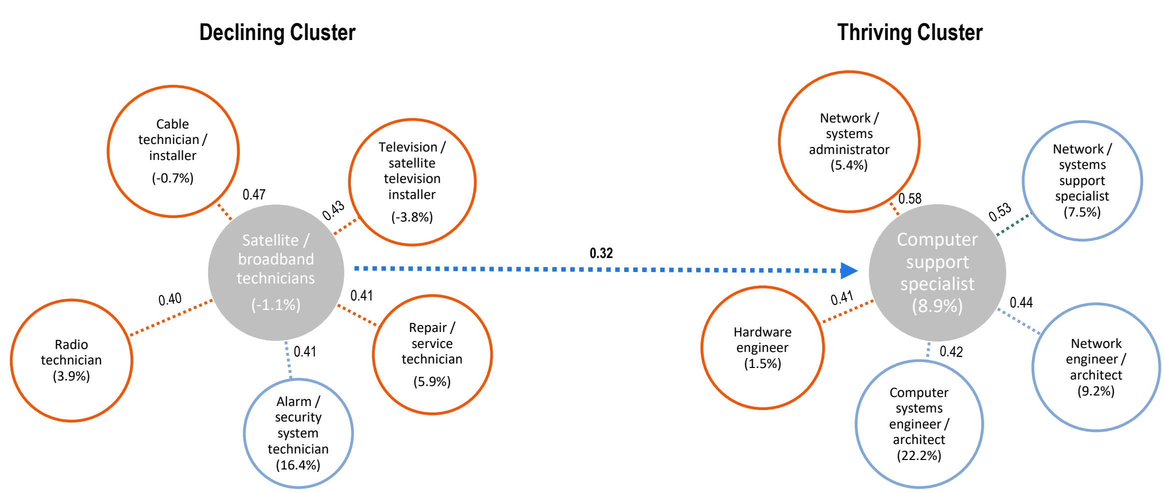
7.2. Satellite / broadband technicians and computer support specialists: Occupational clusters and retraining pathways

7.2.1. Occupation clusters for satellite / broadband technicians and computer support specialists

Satellite / broadband technicians have already seen their jobs transforming partly due to the arrival of artificial intelligence. Although some of their tasks still require physical presence (e.g. physical installation of equipment), another part of it is being complemented (or replaced) by the advent of artificial intelligence. For instance, telecommunications companies have turned to virtual assistants to offer solutions to customers' queries. Virtual assistants automate and scale responses to these requests. Another increasing practice relates to the use of virtual assistants to help customers deal with support requests for installation, configuration, troubleshooting, and maintenance, which traditionally was a central part of technicians' work. With artificial intelligence, operators can teach customers how to install and operate their own devices. In this rapidly changing context, according to the US Bureau of Labour Statistics (US Bureau of Labor Statistics, 2021[4]), employment for telecommunications equipment installers and repairers will decrease by 1.1% between 2020 and 2030, a projection that is far below the expected average growth of employment over the period for the whole economy.

Technological change and automation is negatively affecting the jobs of satellite and broadband technicians but this also extends to those occupations that share with it a high degree of skill similarity which face negative employment projections with the exception of alarm / security system technicians.[3] Figure 7.3 shows the occupation cluster for satellite / broadband technicians (that is the occupation sharing the highest degree of skill similarity with them). Out of the five closest occupations in terms of skill requirements, employment is projected to grow at slower pace than average in four of them. Negative employment growth is projected for cable technicians / installers (-0.7%) and television / satellite / television installers (-3.8%). Employment for radio technicians and repair / service technicians is expected to be positive but lower than average (3.9% and 5.9%, respectively).

Figure 7.3. Occupation clusters: Satellite / broadband technicians to computer support specialists



Note: The figure shows the two occupation clusters for i) satellite broadband technicians on the left and ii) compute support specialists on the right. The most similar occupations to the one shown in the centre of each cluster are identified by a dashed line above which the occupational similarity index is placed. Higher values of the occupational similarity indicate a higher degree of skill overlap between origin and destination. BLS employment projections for the period 2020-30 are indicated in brackets within each bubble/occupation. The blue line connects the two occupation clusters, highlighting potential career pathways from declining to thriving occupations.
Source: OECD calculations based on Lightcast data; and US Bureau of Labor Statistics (2021[4]).

Technological change represents a challenge for workers employed in many routine and medium-skilled occupations, that is also an opportunity to be leveraged to move to safer careers in the future through adequate retraining and upskilling.

The right panel of Figure 7.3 identifies the 5 digital occupations that are closest to satellite and broadband technicians in terms of skill requirements and that could potentially represent interesting career moves. The analysis of skill demands contained in online job postings shows that the closest career transition towards a digital occupation would be to computer support specialists whose employment is projected to grow by 8.9% between 2020 and 2030.

In ways similar to satellite and broadband technicians, computer support specialists are in charge of providing technical support to companies, organisations and customers on computer software and equipment. They also supervise computer systems and work on repairs when needed. Their skills entail knowledge of telecommunications, engineering and technology.

Table 7.3 ranks the most relevant skills for computer support specialists by the intensity of the training that satellite and broadband technicians should undertake to move into that occupation. Results indicate that satellite and broadband technicians would be required to upskill significantly in Helpdesk support and IT management, boosting their ability to assist and inform user on electronic or computer-related issues and to manage IT resources according to a firm's needs and priorities.

Along with the above skills, satellite and broadband technicians will need to boost their knowledge of technical aspects such as the knowledge of internet and border gateway protocols (i.e. the network layer communications protocol in the Internet protocol suite for relaying datagrams across network boundaries). Similarly, some training will be needed in hardware asset and enterprise mobility management as computer support specialists focus are typically requested to support the management of mobile devices, wireless networks, and other mobile computing services in a business context. Providing broad technical support is also an area where some minor upskilling would be needed, but the effort needed in this area is minimal compared to the rest of skills as satellite and broadband technicians are already typically required to provide such support in their daily tasks.

Table 7.3. Retraining pathways: Acquiring the necessary skills, competences and knowledge in technologies to move from satellite / broadband technicians to computer support specialists

Skill distance between origin and destination occupations, selection of the 10 most relevant skills at the destination occupation in the United States

	Skill distance from **origin** to **destination**
Help Desk Support	0.310
Internet Protocols	0.298
IT Management	0.271
Administration of Accounts	0.243
Border Gateway Protocol	0.224
Hardware Asset Management	0.216
Enterprise Mobility Management	0.201
Airwatch	0.167
Virtual Local Area Networks	0.144
Technical Support	0.061

Note: The skill distance between the origin and destination occupation is computed as the difference between the skill relevance of each skill between the two occupations. Skill relevance scores are derived applying natural language processing algorithms to the information contained in OJPs as detailed in Annex 3.A in this report.
Source: OECD calculations based on Lightcast data for the United States in 2019.

While computer support specialists represent the shortest transition to a digital occupation for satellite and broadband technicians, other occupations (Figure 7.3, right panel) are also possible career moves into digital professions, where the retraining would be still acceptable and the skill distance relatively manageable.

Occupations that share a high degree of skill similarity with computer support specialists (and that are not too distant from satellite and broadband technicians) are, for instance, network / systems administrators, network / systems support specialists, network / engineer architects or computer systems engineers / architects. All those occupations are expected to grow positively. Computer systems engineers, in particular, are expected to grow by more than 22% in the next decade in the United States, potentially creating skill gaps and bottlenecks that could be filled by workers in other parts of the economy undertaking retraining and upskilling in their core skills and competences.

7.3. Customer service managers and data engineers: Occupation clusters and retraining pathways

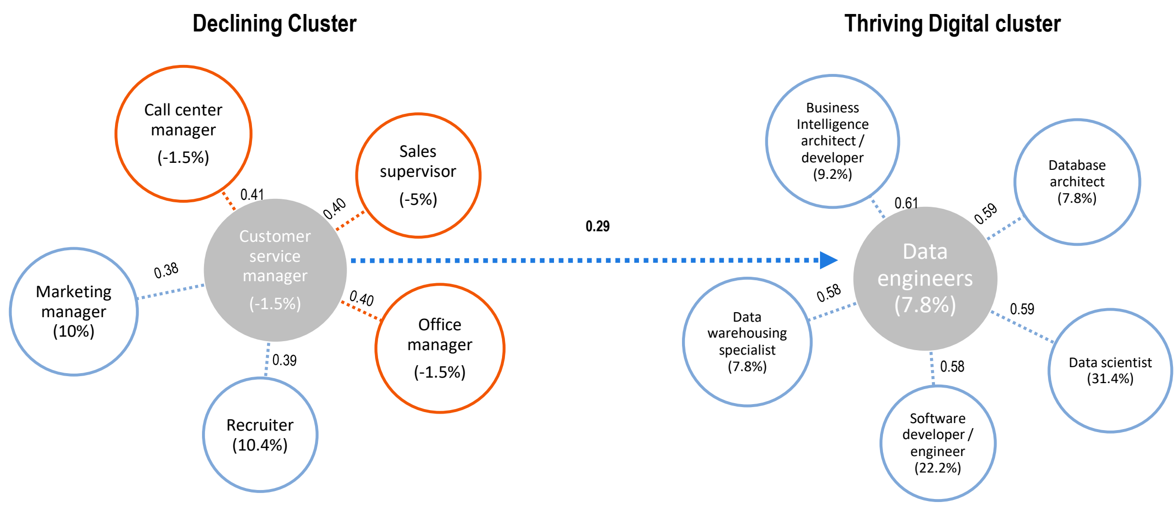
7.3.1. Occupation clusters for customer service managers and data engineers

The advent of digitalisation and the vastly increased ability of automated AI-powered algorithms to provide precise information to customers, is also affecting several customer-service occupations that, up until now, have been traditionally carried out by human labour. For some of those roles, automation – triggered by digitalisation – is likely to lead to a significant reduction in employment. One such example of automation affecting the customer service sector is the use of chatbots. It is common today, in fact, that customers who navigate a firm's webpage in search of information interact with a software that is capable of providing useful assistance and precise answers to customers' questions. This is possible thanks to the development of machine learning techniques, which allow computers to learn information without being explicitly programmed and enable them to ask questions to customers and answer to customers' queries using artificial intelligence. The US BLS, for instance, points out that "*There is expected to be less demand for customer service representatives, especially in retail trade, as their tasks continue to be automated. Self-service systems, social media, and mobile applications enable customers to do simple tasks without interacting with a representative. Advancements in technology will gradually allow these automated systems to do even more tasks. Some companies will continue to use in-house service centers to differentiate themselves from competitors, particularly for complex inquiries such as refunding accounts or confirming insurance coverage*" (Bureau of Labor Statistics, n.d.[5]).

In part as a consequence of these trends, also jobs for customer service managers are projected to decline in the next decade[4] by -1.5%. The tasks carried out by customer service managers mainly involve overseeing teams of people responding to inquiries from customers but since most of those teams are shrinking in size as AI is deployed to respond automatically to customers, the relevance of customer service managers is also expected to decrease significantly in the future.

Customer service workers therefore may soon need to consider retraining and upskilling pathways with a view to experiment career changes and transition to jobs that are safer in the labour market. The left panel of Figure 7.4[5] presents the five occupations that share the most similar skill requirements with Customer service managers and that belong to its "occupation cluster". The right panel of Figure 7.4, instead, presents those digital occupations towards which customer service managers could transit to with some moderate retraining.

Figure 7.4. Occupation clusters: Customer service managers and data engineers



Note: The figure shows the two occupation clusters for i) customer service managers on the left and ii) data engineers on the right. The most similar occupations to the one shown in the centre of each cluster are identified by a dashed line above which the occupational similarity index is placed. Higher values of the occupational similarity indicate a higher degree of skill overlap between origin and destination. BLS employment projections for the period 2020-30 are indicated in brackets within each bubble/occupation. The blue line connects the two occupation clusters, highlighting potential career pathways from declining to thriving occupations.
Source: OECD calculations based on Lightcast data; and US Bureau of Labor Statistics (2021[4]).

It is worth noting that the occupations that share the highest level of skill similarity with customer service managers (i.e. call centre managers, sales supervisors, office managers, recruiters and marketing managers) belong to a "declining occupational cluster" as employment in most of those jobs is projected to decrease in the next decade.[6]

Call centre managers, for instance, share skills of very similar nature to those required by customer service managers, in particular those related to communication and interpersonal skills needed to manage teams and aimed at providing solutions to customers but are projected to decline by 1.5% in the next decade. Sales supervisors are also relatively close to customer service managers in their underlying skill requirements, being responsible for the activities of sales representatives in promoting and selling a product by phone or email. As in the case of customer service managers, they are also required to exhibit managerial skills to train their staff in communicating with customers. Similarly, employment in this occupation is expected to shrink considerably, (-5%) by 2030.

Office managers responsible for organising and co-ordinating office operations, as well as providing administrative support also share similar skills with Customer service managers namely those related with problem solving, initiative and relationship-building skills and are also expected to decline by 1.5% in the next decade.

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While the employment in many of the jobs that share a high degree of skill similarity with customer service managers is expected to decline, other options could be to transit to similar jobs such as recruiters or marketing managers (see Box 7.4) or to boost one's digital skill to move towards digital occupations that are thriving in the labour market and expected to grow significantly in the future.

Box 7.4. Customer service managers and career transitions towards recruiters and marketing managers

Recruiters and marketing managers share a high degree of skill similarity with customer service managers and, contrary to other occupations in that "skill neighbourhood" they are instead projected to grow in the future. When examining their tasks, recruiters (whose employment is projected to increase significantly – 10.4% – in the next decade) are responsible for finding qualified candidates for a job opening by ensuring that the person meets the demands of employer and employee throughout the hiring process. Recruiters are, therefore, required to have strong communication skills and listening skills, which are also important for customer service managers and justify the closeness between the two occupations.

Similarly, the analysis of jobs postings suggests that marketing managers are relatively close to customer service managers as several of their skill requirements overlap. Marketing managers plan programs to generate interest in products or services, and their customer-oriented and managerial skills explain why this occupation is relatively close to customer service managers. Employment for marketing managers is also projected to rise by 10% and they could constitute interesting career options for workers currently employed as customer service managers.

Technological change is responsible for some of the trends leading to a decrease in demand for customer service managers. Retraining and upskilling in digital competences, however, could allow workers employed in those declining jobs to move to careers that are safer in the labour market and with a bright employment outlook.

Among the digital occupations analysed in this report, the shortest transition from customer service managers to a digital occupation would be towards data engineers[7] whose employment is expected to grow significantly (approximately 8%) by 2030 in the United States.

A career transition from customer service managers to data engineers requires the acquisition of a number of digital skills, many of which may require some significant upskilling or retraining. Amongst the pairs of occupations analysed in this chapter, the transition between customer service managers and data engineers is the one that will typically require the highest intensity of retraining as the two occupations are relatively far apart in terms of underlying skill requirements.

Table 7.4 shows ranks the most relevant skills for a data engineer by the intensity of the training needed to a customer service manager to transit to it. Results show, for instance, that significant training would be needed in the knowledge of distributed computing[8] for customer service managers to catch up with the level required to access a profession as a data engineer.

Similarly, significant retraining would be needed in data warehousing and big data, as those represent core skills and knowledge areas for data engineers, but are less frequently used by the typical customer service manager.

Some skills, however, show a stronger overlap between the origin and destination occupation. The knowledge of HiveQL and Microsoft Certified Professional Azure technologies is very relevant for data engineers but the same are also sometimes used in particular tasks performed by customer service managers, in particular when managing large quantities of customer data, justifying a somewhat relatively less intense (though still considerable) need for retraining in case of a career transition between the two roles.

Table 7.4. Retraining pathways: Acquiring the necessary skills, competences and knowledge in technologies to move from customer service manager to data engineer

Skill distance between origin and destination occupations, selection of the 10 most relevant skills at the destination occupation in the United States

	Skill distance from **origin** to **destination**
Distributed Computing	0.535
Data Warehousing	0.472
Big Data	0.466
Apache Hive	0.462
Java	0.437
Apache Impala	0.413
Data Visualization	0.345
Middleware	0.327
HiveQL	0.276
Microsoft Certified Prof. Azure	0.262

Note: The skill distance between the origin and destination occupation is computed as the difference between the skill relevance of each skill between the two occupations. Skill relevance scores are derived applying natural language processing algorithms to the information contained in OJPs as detailed in Annex 3.A in this report.
Source: OECD calculations based on Lightcast data for the United States in 2019.

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Notes

[1] Employment projections come from the US Bureau of Labor Statistics which provides granular employment data that can be used jointly with the information coming from online job postings.

[2] Similar dynamics are expected, however, to hold for other countries.

[3] Differently from other occupations that share a high degree of skill similarity with satellite and broadband technicians, employment for alarm / security system technician is projected to grow significantly in the future (16.4%) and this, then, represents interesting career options for workers in the cluster.

[4] Customer service managers belong to an occupational group (SOC 43-1011) that is projected to decline by 1.5 in employment terms, according to the US Bureau of Labor Statistics projections for 2020-30 (US Bureau of Labor Statistics, 2021[4]). It should be noted that BLS projections are made at the 6th digit level, while customer service managers is the job title used by Lightcast at the 8th digit level within SOC 43-1011).

[5] The numbers next to the dashed lines in the figure indicate the closeness of the occupation with respect to customer service managers.

[6] Employment projections used in this chapter refer to the United States in between 2020 and 2030.

[7] Data engineers "administer, test, and implement computer databases, applying knowledge of database management systems. Co-ordinate changes to computer databases. May plan, co-ordinate, and implement security measures to safeguard computer databases" (US Bureau of Labor Statistics, 2021[4]).

[8] Distributed computing consists of enabling multiple software components that are on a number of computers to run as a single system, with computers being either physically close together and connected by a local network, or geographically distant and connected by a wide area network (IBM, 2021[6]).

Skills for the Digital Transition

ASSESSING RECENT TRENDS USING BIG DATA

This report presents the most recent trends in the labour market demand for digital professionals and skills, highlighting where bottlenecks are emerging and policy action is – and will be – needed to support individuals who aim to thrive in the digital transition. The report analyses a wide range of digital occupations and the associated skill and technology demands using a unique set of data collected from millions of job postings published online in Belgium, Canada, France, Germany, Italy, the Netherlands, the United Kingdom, the United States, Singapore and Spain. The evidence contained in this report is key for governments to design targeted retraining and upskilling policies, and for workers to fully benefit from the digital transition.

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