5 Navigating skill demands in turbulent times

This chapter presents evidence on the widespread impact of the COVID-19 pandemic on OECD labour markets by tracking the evolution of job postings published on line. The results indicate that the pandemic had heterogeneous effects on postings aimed at high- and low-skilled workers, and led to a surge in vacancies requiring employees to work remotely. The chapter discusses how, in the midst of such an uncertain period, workers need to become resilient by enhancing their ability to adapt to change. It explores new indicators identifying transversal skills, and the specific wage and employment returns these yield in the labour market. Looking ahead, the chapter analyses which occupations and skills are expected to increase or decrease in demand owing to megatrends, and proposes pathways for retraining workers who are most likely to be exposed to disruption.

Introduction

Learning, skill development and societal changes are intertwined. Individuals spend a large part of their lives in educational settings, acquiring life skills and preparing for a career. Once in work and society, skilled individuals are the driving force for change as they discover new ways to produce, organise work and have a meaningful impact on society. Change, in turn, is reflected in new skill demands as societies and labour markets evolve.

Change can either be abrupt and unexpected or take time to materialise, giving people the chance to anticipate and adjust to it. The COVID-19 crisis was a sudden and unprecedented event that dramatically transformed the life of virtually every person around the world. Fear of infection, strict public health guidelines and great uncertainty produced a sharp and sudden contraction in economic activity. The result was a deep and widespread shock to the labour market, with a serious impact on the demand for skills. Many industries were forced to cease operations to protect their workers' health and comply with policies aiming to contain the virus. Whenever possible, employers reorganised their operations to facilitate remote working, but many individuals lost their jobs and livelihoods. At the same time, the health crisis created shortages of workers in specific occupations (mainly healthcare and public safety), and labour markets and governments struggled to find skilled professionals to fill the gaps.

Before the COVID-19 pandemic, globalisation, technological changes, automation, digitalisation, artificial intelligence and big data as well as population ageing were already reshaping societies and the world of work at a breakneck speed. OECD estimates issued before the crisis projected that around 15% of current jobs would disappear owing to automation, and another 32% would require substantially different tasks and skills over the next 15 to 20 years (Nedelkoska and Quintini, 2018[1]). Those driving forces (megatrends) did not come to a sudden stop with the pandemic. Instead, they will likely compound the effects of the COVID-19 crisis, accelerating changes in the way work is organised, and skills are used and demanded in labour markets.

Inevitably, the types of skills individuals need to master today differ from those they will need in the future. Lifelong learning systems play a fundamental role in bridging the distance between current skill needs and future demands by helping individuals anticipate changes, develop new skills and perfect others. Some skills can help individuals respond to both current and future skill demands equally. Transversal skills, such as complex problem solving, analytical skills and creativity, allow people to adapt to different situations and unexpected changes. They promote resilience and help individuals navigate both current and future labour markets and societies. Adopting a lifelong learning perspective, this chapter investigates three stages of skill development.

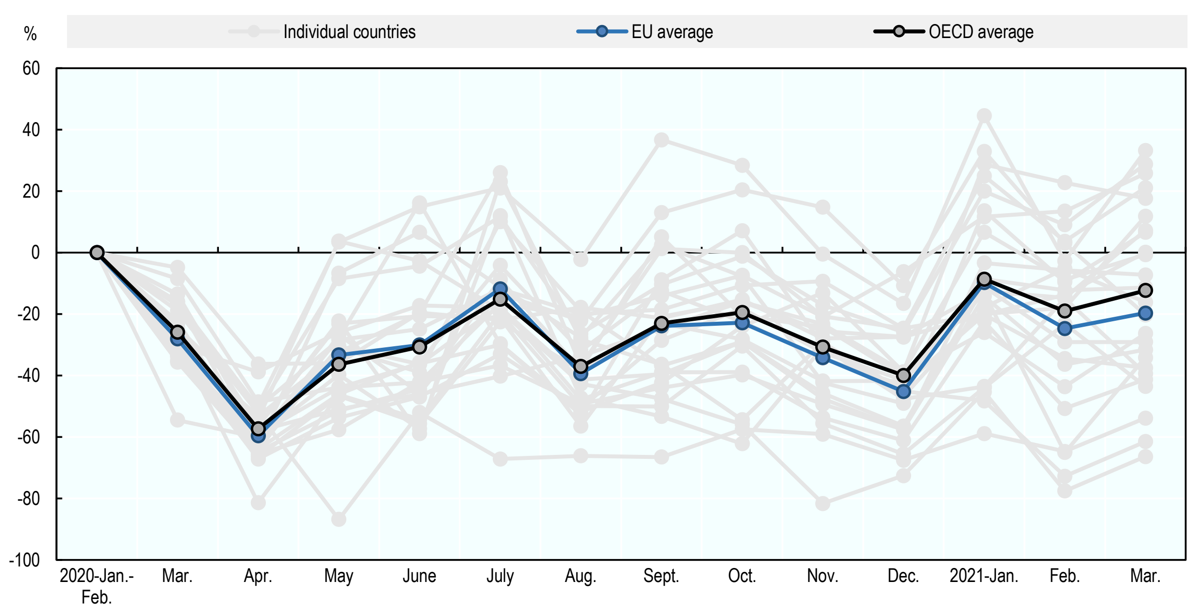
First, the chapter looks at the "urgency of now", analysing the impact of the COVID-19 crisis on current skill demands and the reactions of economies around the globe. Second, the chapter looks into the future, assessing how skill demands are projected to change owing to megatrends such as population ageing, digitalisation and technological progress. It reviews the jobs that are projected to grow in the next 10 years and their associated skill requirements. Third, the chapter considers the interconnection between current and future skill demands, and the role transversal skills can play in connecting different stages of life. It proposes an innovative strategy to identify transversal skills, parsing the text used by employers to describe job offers on line. The results presented in this chapter emphasise the importance of lifelong learning as a tool to mitigate unpredictable shocks (such as the COVID-19 crisis) and anticipate the expected disruption resulting from structural megatrends. The chapter also highlights the potential of blending traditional statistics with more innovative approaches relying on the analysis of big data and online vacancies. Looking forward, these blended approaches will become increasingly important to understand with unprecedented timeliness and granularity the impacts of both sudden shocks and future trends.

The "urgency of now": An assessment of the impact of the COVID-19 pandemic on labour-market and skill demands using online vacancies

The COVID-19 crisis is transforming the lives of all individuals around the globe. The severe consequences on public health have been matched by sharp declines in economic activity and upheavals in labour markets. Preliminary evidence suggests that COVID-19 has had a considerably vaster impact than the 2008 Great Financial Crisis (e.g. OECD (2020[2])). The analysis in this chapter confirms these results as it explores the evolution of vacancies published on line across a range of countries during the pandemic (see Annex 5.A for more details on the data sources and methodology used for the analysis).

Figure 5.1 presents the observed change in the number of job postings published on line between March 2020 and March 2021. It compares the volume of jobs advertised on line during the pandemic to the period spanning January-February 2020, immediately before its first effects came to light. The figure shows that the number of new jobs posted on line, on average across the OECD, dropped by approximately 60% by April 2020. Croatia, Denmark and the Slovak Republic experienced among the sharpest declines in job postings in the initial period of the pandemic (March-May 2020). In France, the Netherlands and the United States, the contraction in job offers posted on line was milder – although still substantial. By July 2020, several countries experienced a relative improvement, with a reduction in the contraction of new jobs published on line. However, total jobs published on line at the end of March 2021 were still considerably lower than during the pre-crisis period in a variety of countries.

Figure 5.1. Evolution of online job vacancies



Note: The figure shows the percentage change in the number of online job postings by country relative to the pre-crisis period (i.e. average of January and February 2020). Belgium, Finland, Hungary, Malta, New Zealand, Portugal and Sweden are omitted from the analysis due to small sample size or high volatility observed in the studied period. Country-specific results are available from the Statlink below.
Source: OECD calculations based on data from Burning Glass Technologies, May 2021.

StatLink https://stat.link/1pza7e

As the SARS-CoV-2 virus began to spread, virtually all countries worldwide introduced containment and mitigation strategies, such as limiting the movement and travel of individuals, closing schools and other educational institutions, halting non-essential activities and postponing non-essential medical procedures[1] (Bai et al., 2020[3]). Although the exact nature, timing, scope and intensity of responses varied substantially across countries – and sometimes even within countries (Hale et al., 2020[4]) – the containment measures inevitably had a profound impact on labour markets.

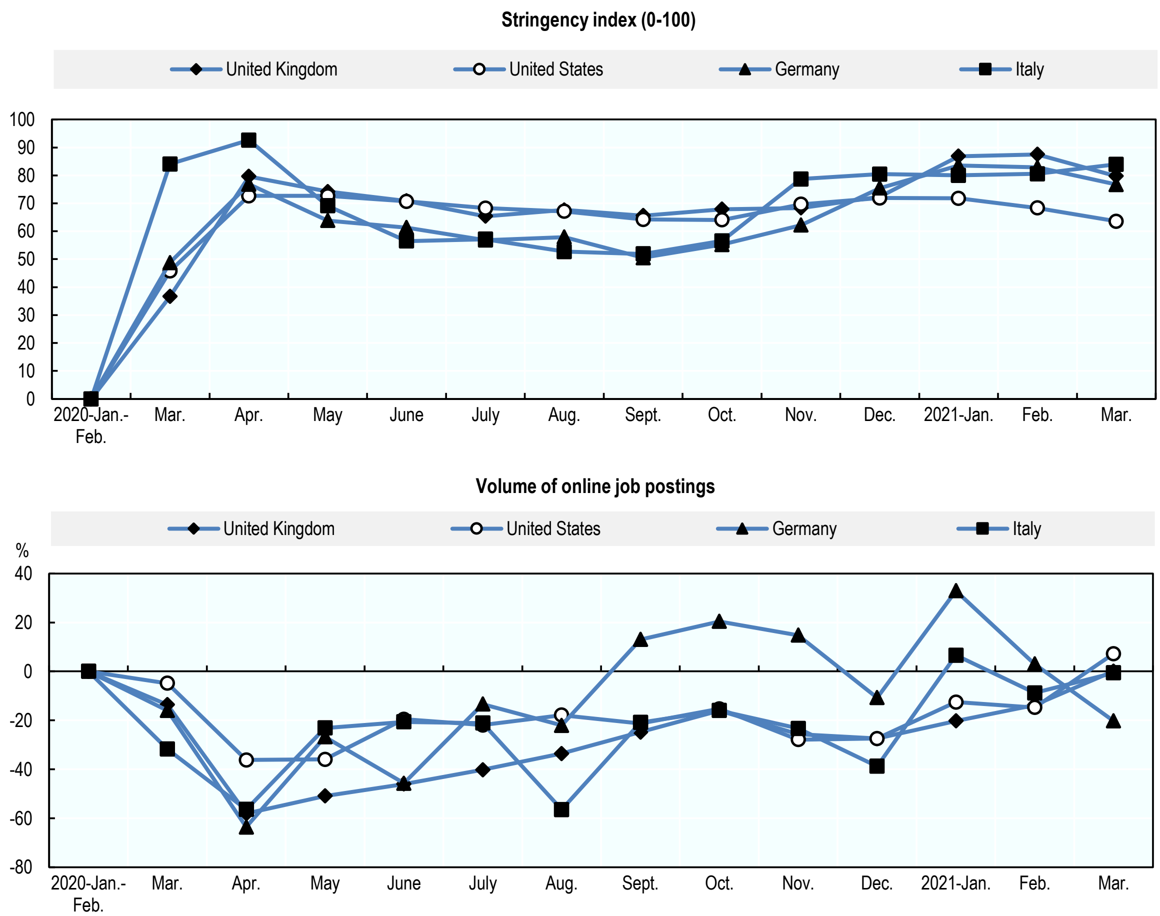
Figure 5.2 illustrates both the stringency of national measures adopted during the crisis and the evolution of online job postings in the corresponding countries.[2] The upper panel of Figure 5.2 presents the "stringency index", a composite measure of the number and strictness of government policies (e.g. school closures, limitations to the size of public gatherings, restrictions on freedom of movement within a country in terms of timing and distance travelled, workplace closures and travel bans). The stringency index ranges from 0 to 100, with 100 indicating the highest degree of strictness.[3] The lower panel of Figure 5.2 presents the evolution of online job postings relative to the pre-crisis period of January-February 2020. The results show a clear association between the sharp increase in policy stringency (corresponding to the implementation of lockdowns around March 2020) and the decline in online job postings until April 2020. In later months (starting from May 2020), some countries (e.g. Italy and Germany) eased restrictions. Correspondingly, the volume of online job postings started to recover, but with extreme volatility over time and a more tenuous association with the intensity of the stringency index between May 2020 and March 2021.

Different (and in some cases competing) factors could explain a weaker correlation between policy stringency and the evolution of online vacancies beyond the initial phase of the pandemic. First, some businesses may have ceased operations permanently during government-imposed restrictions. Second, even after some regulations were relaxed, many employers may have chosen to defer new hiring as new measures could be imposed if viral transmission increased. Third, aggregate economic demand – a key driver of labour demand – may not have increased as soon as restrictions were eased, because some customers were reluctant to revert to pre-crisis spending levels owing to job uncertainty or loss of income during generalised closures.

At the moment of writing this report, governments are delivering vaccines to the general population, starting with at-risk groups and frontline workers. Containment measures are still likely to remain in place as long as the virus keeps spreading at considerable speed. Thus, economic activity and new job postings should remain well below their pre-crisis period until the number of infections is brought under control.

Figure 5.2. Stringency of COVID-19 measures and online job postings

Germany, Italy, United States and United Kingdom, 2020 and 2021 (Q1)



Note: The top panel shows the evolution of stringency index (monthly averages) taken from the Oxford COVID-19 Government Response Tracker (OxCGRT), a systematic way to track government responses to COVID-19 across countries and sub-national jurisdictions over time.
The bottom panel shows the percentage change in the number of online job postings relative to the pre-crisis period (i.e. average of January and February 2020) for selected countries.
Source: OECD calculations based on data from Burning Glass Technologies, May 2021; Hale et al. (2020[4]), Oxford COVID-19 Government Response Tracker, https://covidtracker.bsg.ox.ac.uk/.

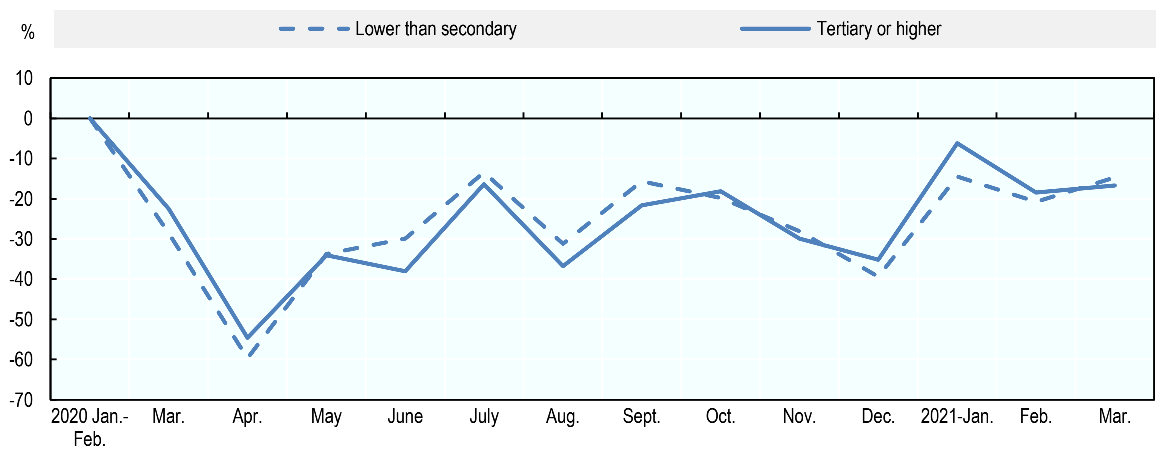
StatLink https://stat.link/gifxvm

The impact of the COVID-19 crisis on the number of online vacancies varies by educational level

While the COVID-19 pandemic hit virtually all sectors of the economy simultaneously, the analysis of online vacancies suggests that many low-paid and often low-educated workers were particularly affected during the initial phase of the COVID-19 crisis. Figure 5.3 compares the volume of job postings in 2020 and the first quarter of 2021 to the pre-crisis period (January-February 2020), disaggregating the change in job advertisements according to the required educational level stated in the vacancy posted on line. The results show that, on average, new online job postings requiring a secondary education (or lower) decreased more than those requiring tertiary education at the start of the pandemic while, as the pandemic progressed, the reverse occurred. In other words, in March and April 2020 the drop in new jobs was sharper for low-skilled jobs while in later periods it was sharper among high-skilled jobs.[4]

Figure 5.3. Evolution of job postings by educational level, OECD average

March 2020 – March 2021



Note: The figure shows the percentage change in the number of average monthly online job postings between March 2020 and March 2021, relative to the pre-crisis period (i.e. average of January and February 2020) by minimum education level required of either secondary or lower and tertiary of higher. Job postings that lack information on education requirements were discarded. The OECD average is unweighted and Belgium, Croatia, Czech Republic, Denmark, Finland, Hungary, Malta, New Zealand, Poland, Portugal, and Sweden have been dropped due to small sample size or high volatility observed in the data.
Source: OECD calculations based on data from Burning Glass Technologies, May 2021.

StatLink https://stat.link/jqy291

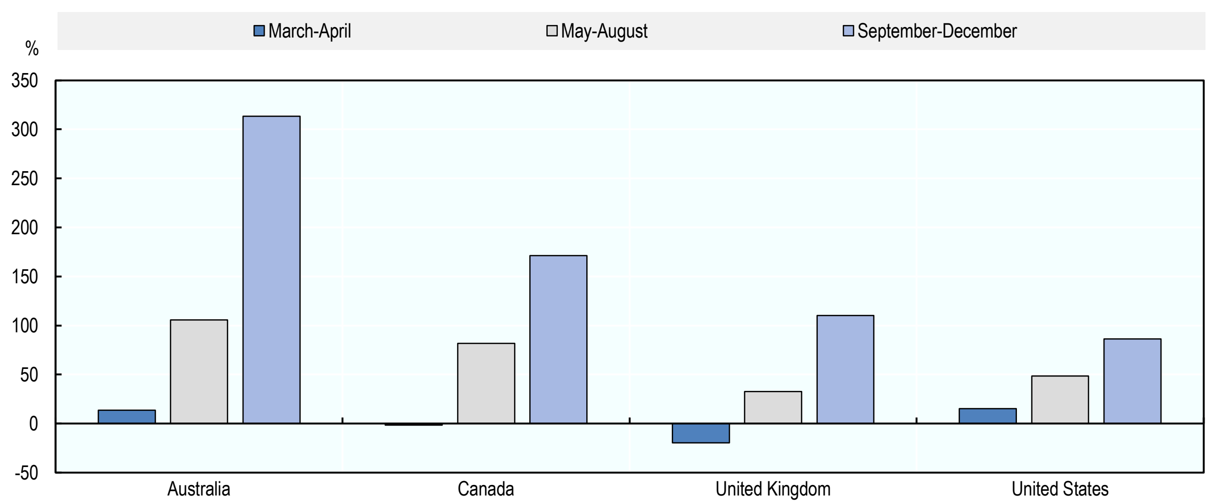
The share of online job openings requiring working from home increased markedly from mid-March 2020 onwards

Numerous studies have attempted to estimate the jobs that can be performed directly from home (e.g. Dingel and Neiman (2020[5]); Espinoza and Reznikova (2020[6])). The results of this strand of literature indicate that around 30% of individuals across OECD countries can perform job-related tasks remotely (Espinoza and Reznikova, 2020[6]). These studies have typically analysed the tasks performed by workers in various occupations and indirectly inferred the degree to which tasks in broad occupational groups can be performed remotely, based on tasks that were performed before the crisis (Dingel and Neiman, 2020[5]). The analysis of the information contained in online vacancies, instead, makes it possible to determine whether the individual vacancies require the person to work from home, as explicitly stated by the employer in the job posting.

The results of this analysis (Figure 5.4) show that during the COVID-19 health crisis, working-from-home arrangements gained traction relative to the pre-crisis period, in line with evidence from Galasso and Foucault (2020[7]) and OECD (2020[2]). Remote working arrangements helped maintain a degree of economic activity in those sectors and occupations that could reorganise their operations to comply with sheltering-in-place regulations or social distancing guidelines.

In Australia, the number of new job postings requiring individuals to work from home has steadily increased since the onset of the crisis, doubling in size between May and August 2020 and increasing even further up until the end of 2020. Other countries, particularly the United Kingdom and Canada, have also seen a considerable increase in online vacancies requiring such arrangements relative to the pre-crisis period (January-February 2020). It is too early to assess whether this trend will persist once the infection is brought under control and mitigation policies have eased. However, digitalisation was already growing and permeating the economy prior to the crisis, and these dynamics are certain to continue. A survey of employers conducted by the World Economic Forum (2020[8]) indicates, for instance, that large firms plan to expand remote working arrangements, with the potential to move 44% of their workforce to operate remotely.

Figure 5.4. Evolution of job postings by "working-from-home" requirement, 2020



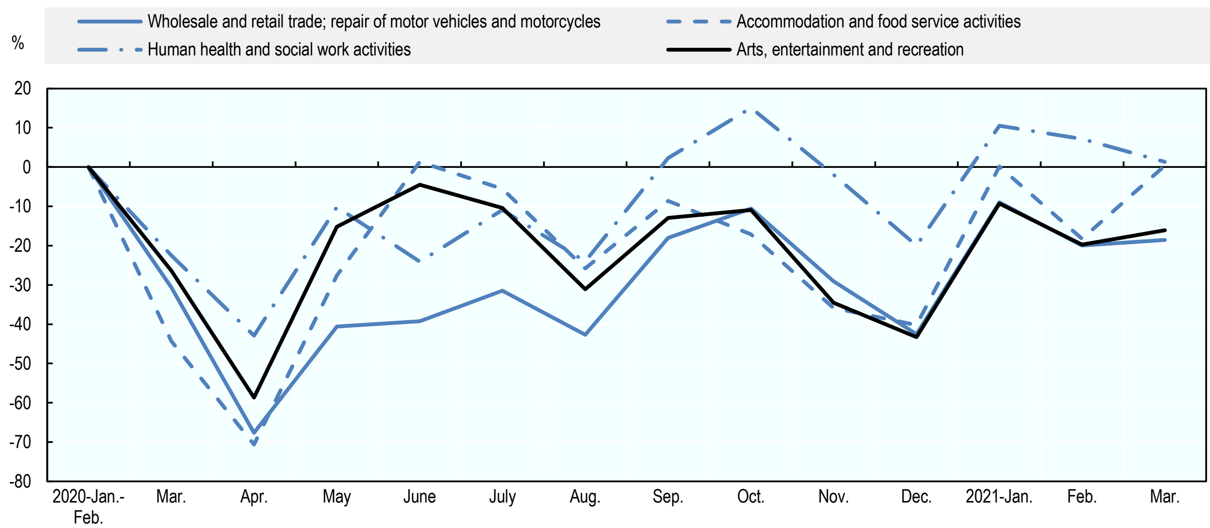
Note: The figure shows the percentage change in monthly online job postings with working-from-home requirement, relative to the pre-crisis period (i.e. average of January and February 2020). EU countries are not included due to the lack of information on working-from-home requirement. New Zealand is dropped owing to small sample size. Data for the United States come from the Burning Glass Technologies' Labor Insight online tool and are averaged monthly. For the United States only, the latest period covers August-October 2020.
Source: OECD calculations based on data from Burning Glass Technologies, May 2021; Burning Glass Technologies (2020[9]), Labor Insight, https://www.burning-glass.com/products/labor-insight/.

StatLink https://stat.link/aten07

Online job postings declined in some sectors and occupations more than in others

Although the volume of online job postings has declined in virtually every sector, heterogeneity exists across sectors. Some industries and sectors maintained most of their operations and sometimes even experienced a surge in demand, while others were forced to reduce or halt their operations. Figure 5.5 indicates that, on average across European countries for which information is available, the healthcare and social assistance sectors experienced a milder decline relative to other sectors. While the drop in new vacancies in this sector was very significant at the onset of the pandemic, the gap relative to the pre-pandemic period closed already in May and June 2020. In August of the same year the number of new job postings in the sector exceeded the average of January and February 2020, signalling the strong demand for healthcare professionals. Jobs in the wholesale and retail trade sector, instead, dropped significantly at the beginning of the pandemic and are only slowly starting to recover in recent months. A similar pattern is observed in accommodation and food service activities where online job postings dropped by a staggering 70% in April 2020 and recovered only in recent months. Jobs in the arts, entertainment and recreation sector are still below the pre-crisis level.

Figure 5.5. Evolution of online job postings by sector, European Union average (selection)

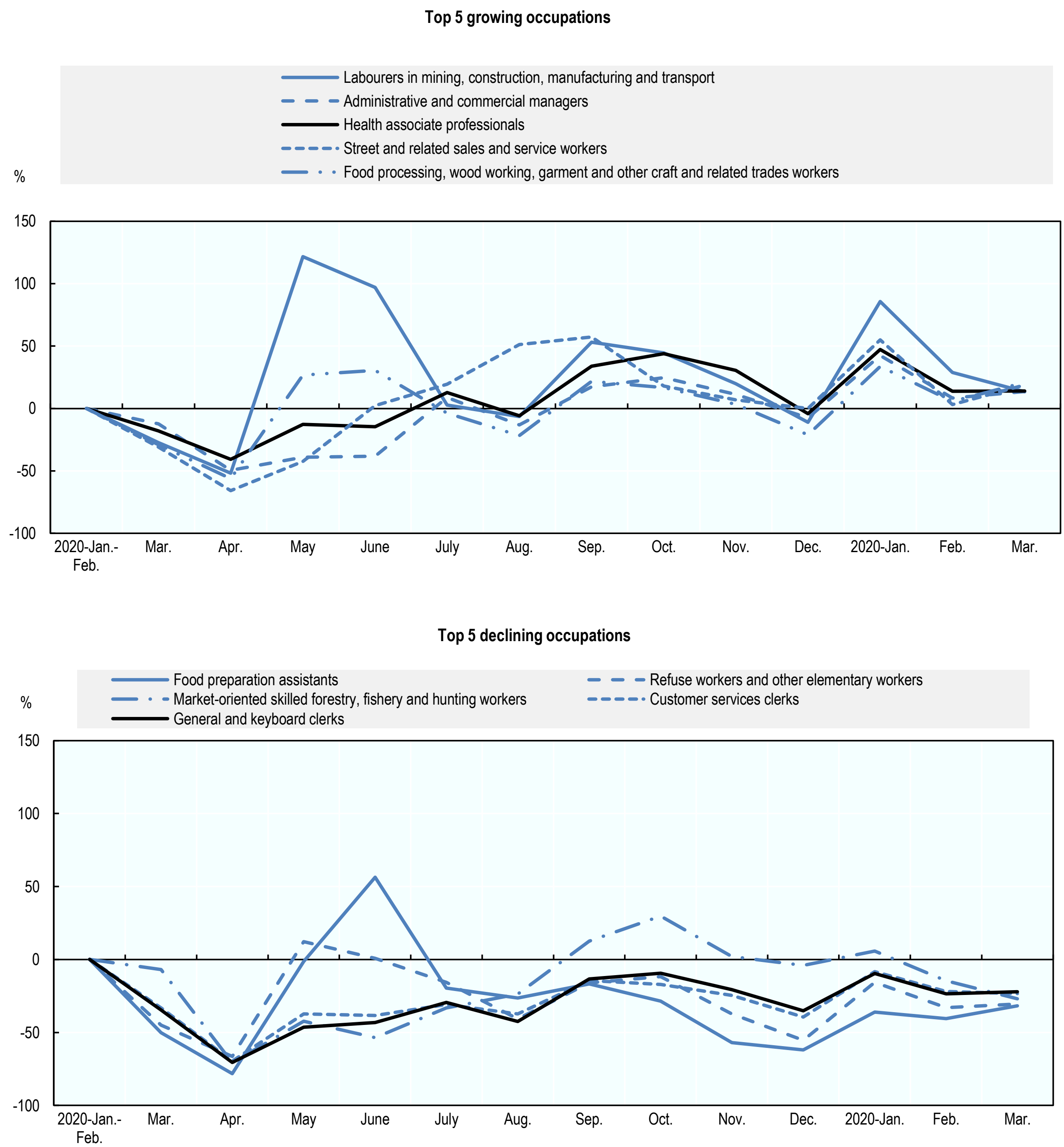


Note: The figure shows the percentage change in the number of online job postings for the EU-average, relative to the pre-crisis period (average of online job postings in January and February 2020) for selected sectors (NACE rev.2, 1 digit). Belgium, Finland, Hungary, Malta, Portugal and Sweden are not included in the calculation of the EU average due to small sample size, or high volatility observed in the data.
Source: OECD calculations based on data from Burning Glass Technologies, May 2021.

StatLink https://stat.link/znf57p

The COVID-19 pandemic has also had a heterogeneous impact on specific occupational groups within sectors (OECD, 2020[10]). The number of online job openings – particularly for occupations such as essential workers, hospital staff, employees of food retailers and warehouse personnel – remained constant or increased, even as policy makers in many countries severely limited economic activities and freedom of movement.

Figure 5.6. Top and bottom occupations by volume of online job postings during the COVID-19 pandemic, European Union



Note: The table shows top five and bottom five occupational groups (2-digit ISCO level) by change in online job postings in between March 2020 and March 2021 compared with respect to the pre-crisis period (i.e. average of online job postings for January and February 2020). Postings missing information on the occupation of affiliation were discarded. Results show the EU27 unweighted average for each occupational group, excluding Belgium, Finland, Hungary, Malta, Portugal and Sweden that have been removed from the analysis due to high volatility observed in the data.

Source: OECD calculations based on Burning Glass Technologies data, May 2021.

StatLink https://stat.link/h52dfq

Figure 5.6 (upper panel) shows the top five occupational groups (2-digit ISCO) that grew the most across job advertisements published on line in between March 2020 and March 2021. Results show that, after the first peak of the pandemic (April-May 2020), the demand for health associate professionals grew steadily across the EU countries analysed exceeding, in March 2021, the pre-pandemic level. In many European countries (including France, Ireland, Italy and Spain), online job openings for occupations such as nurses, personal care workers, medical doctors and medical technicians increased in the months following the onset of the COVID-19 emergency.

Other occupational groups that were not (or only marginally) affected by containment measures and mandatory physical closures registered an increase in job openings, particularly in logistics and distribution. Labourers in mining, construction, and manufacturing and, in particular, the transport sector experienced amongst the highest growth rates in online job postings at the beginning of the pandemic as well as throughout the whole period analysed. In Europe (particularly in Lithuania and Romania), job openings for transport and storage workers increased or remained constant after the onset of the health crisis.

Similarly, in Australia, Canada, the United Kingdom and the United States, demand for professionals such as physicians, nurses, pharmacists, epidemiologists, care assistants and technicians increased strongly. Between March and November 2020, online openings for emergency medical technicians and paramedics in the United Kingdom increased by 34%, and online openings for medical equipment repair technicians grew by 114%. In the United States, online vacancies for physical scientists increased by 10% and demand for epidemiologists and community health workers remained stable, always relative to the beginning of the year.

Online job vacancies in order processing and packaging increased by nearly 50% in the United States compared to the beginning of the year, and advertisements for packaging jobs increased by around 47% in Australia and the United Kingdom. This suggests that online shopping, and the associated delivery of goods directly to customers, have also grown significantly as a result of social distancing measures and the fear of contracting the virus when leaving home.

The various containment measures and closures encouraging individuals to remain home and reduce social interactions led to a decrease in the volume of online postings for jobs involving face-to-face interactions. Figure 5.6 (lower panel) shows the five occupations for which online vacancies decreased most sharply across EU27 countries relative to the pre-crisis period. On average across the EU, online job postings for food processing, wood working, garment and other craft and related trades workers fluctuated significantly, dropping by more almost 80% in April 2020 and remaining, in March 2021, to a level that is approximately 30% below the average volume of online vacancies recorded prior to the pandemic (i.e. January and February 2020). In many European countries, including Italy, Spain, Germany and Denmark, online job postings for waiters and bartenders, cooks and food preparers dropped by as much as 80% over March-July 2020 and, in the United Kingdom, the volume of online vacancies for baristas, bussers and bartenders contracted by 72% over March-November 2020. In Denmark, Spain and Latvia, the number of openings for shop salespersons also declined extensively. General and keyboard clerks as well as customer service clerks also recorded significant decreases in the volume of online job postings during the pandemic, standing in March 2020 at levels that are 20 to 30% lower than those prior to the pandemic.

As mentioned above, occupations in the tourism and leisure sectors were also hit hard. In many European countries, online job postings for client information workers fell by 70% compared to the beginning of the year. In the United States, Canada and the United Kingdom, advertisements seeking travel agents, tour guides or flight attendants dropped by 70-90% over March-November 2020. Online vacancies for bell persons and baggage attendants also decreased considerably in both the United Kingdom and the United States. Similarly, online postings for meeting, convention and event planners dropped by 68% in Australia, 67% in Canada, 83% in the United Kingdom and 79% in the United States.

The role of transversal skills in navigating the labour market

In a rapidly changing world, developing “transversal skills”, i.e. skills that are “not specifically related to a particular job, task, academic discipline or area of knowledge and that can be used in a wide variety of situations and work settings” (UNESCO, 2021[11]) is key if workers are to become resilient to shocks triggered by rapid technological change and megatrends or a sudden and unexpected crisis such as the current pandemic.

Even though previous literature has devoted considerable attention to the study of transversal skills, no clear agreement exists on what transversal skills really are and how they can be measured. Recent studies have used a wide variety of terms (i.e. soft, cognitive and non-cognitive, interpersonal and social skills) interchangeably, and many of those terms/concepts overlap. Similarly, empirical studies have struggled to find robust measures to assess their impact on labour-market outcomes, such as wages and employment prospects.

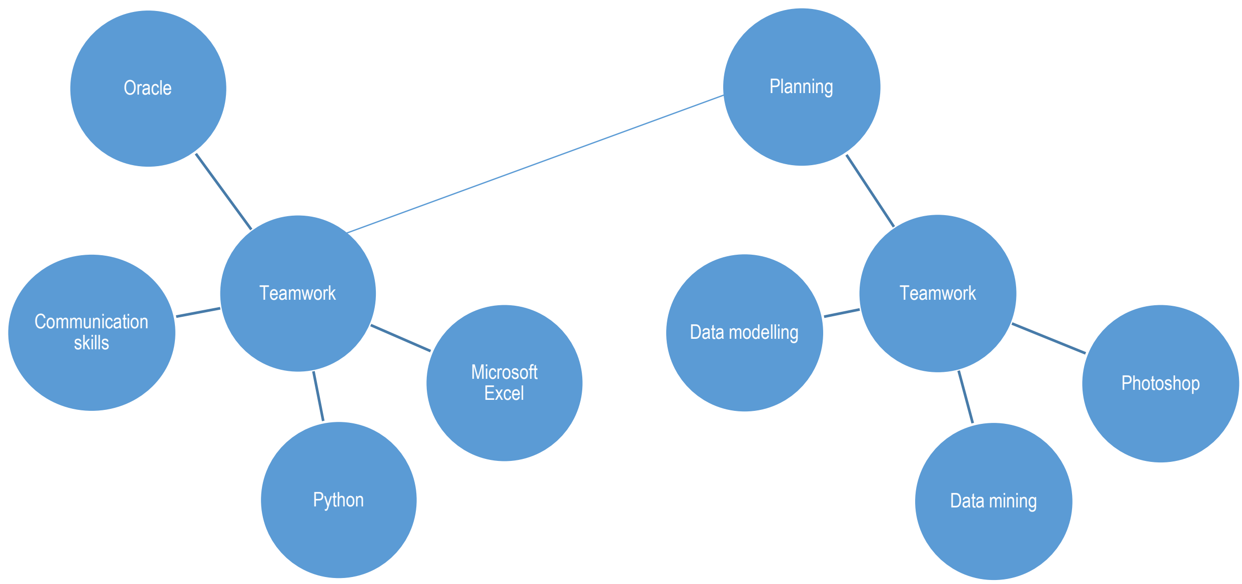
Among the (few) attempts to provide a catalogue of transversal skills, the European Centre for the Development of Vocational Training (Cedefop)'s European skills and Jobs survey (CEDEFOP, n.d.[12]) identifies communication skills, team-working skills, customer handling skills, problem-solving skills, learning skills, and planning and organisational skills as essential “transversal skills”. However, little is said on the precise criteria for selecting these skill keywords or the degree of “transversality” of each skill.

The European Union has also sponsored different Erasmus+ projects to develop catalogues and lists of transversal skills. The Assessment of Transversal Skills (ATS2020, 2021[13]) puts “digital literacy” at the core of its transversal skills framework, along with information literacy, collaboration and communication, creativity and innovation, and autonomous learning. The Keystart2work (n.d.[14]) project lists different keywords, such as decision-making, organisational and time management, and even negotiations skills.

The approach followed in this chapter to identify transversal skills draws upon recent developments in natural language processing (NLP) and machine learning (ML). More precisely, NLP approaches allow transforming textual and semantic information contained in the text of job postings into mathematical values that retain the semantic meaning of the original words (Box 5.1). This approach, initially developed by Google in its PageRank algorithm, makes it possible to qualify the number and importance of the connections among keywords, where more and better-“interconnected” skills are labelled as “transversal” (see also Djumalieva, Lima and Sleeman (2018[15])).

Figure 5.7 provides a simplified example of how skills can connect in a so-called “graph”. Here, the skill keyword “teamwork” is connected to a relatively large number of other keywords – some of which, in turn, are closely connected to a large number of other keywords in the graph (e.g. the case of “planning” skills). The quantity of the connections and their importance (i.e. the number of their further connections) are used to compute the so-called “eigenvector centrality index”, which represents empirically the degree of “transversality” of each skill keyword in the database (Box 5.1).

Figure 5.7. Skill connections and transversality: A graphical example



Note: Bubbles represent examples of keywords collected in online vacancies. Junctures indicate the existence of a relationship between keywords when they are mentioned together in vacancies. The chart is not meant to give a concrete representation of the many different connections among keywords throughout the database as this chart is provided as an example of how keywords may be connected to each other.

Box 5.1. Leveraging machine learning and online job postings to detect transversal skills

Recent developments in NLP allow sophisticated analysis of the information contained in online vacancies. ML algorithms, particularly 'word embeddings', can be used to extract and analyse the relationships between individual skill keywords featured in job postings.

Word-embedding algorithms function by creating a mapping between words and their meaning (semantics) in so-called word vectors. These word vectors are, in practice, the mathematical representation of the semantic meaning of the words in an *n*-dimensional vector space, where words with similar meanings occupy close spatial and mathematical positions. Based on their meaning, for instance, the words "queen" and "king" are likely to have similar word vectors and to be close in the mathematical vector space as they are also semantically related, even if the letters of the alphabet that make up each word are totally different.

From an empirical point of view, estimating word vectors requires "fitting the data" or the "corpus" (i.e. the collection of all words to be analysed – in this case, the texts of millions of job postings) by solving an optimisation problem. The "semantic analysis" relies on identifying the key text elements in the corpus (i.e. the set of all sentences), and assigning those elements to their logical and grammatical role in the semantic context. Word-embedding approaches rely on the theory of linguistics developed in the "distributional hypothesis" (Harris, 1954[16]), which states that words occurring in similar contexts tend to have similar meanings and share common characteristics (Erk, 2012[17]). In semantic analyses, the "context" is obtained by examining the words surrounding the target keyword, which helps understand how the different relationships between keywords represent different relationships between concepts and ideas.

Conveniently, once word vectors are created in the *n*-dimensional space, they can be treated as numerical values, and arithmetic operations/manipulations can be performed with them. Intuitively, these arithmetic operations retain the semantic meaning of words, and the results of such mathematical operations are therefore expected to return semantically and logically meaningful results. For instance, once word vectors have been estimated, the following calculation could be performed:

vec("Madrid") - vec("Spain") + vec("France")

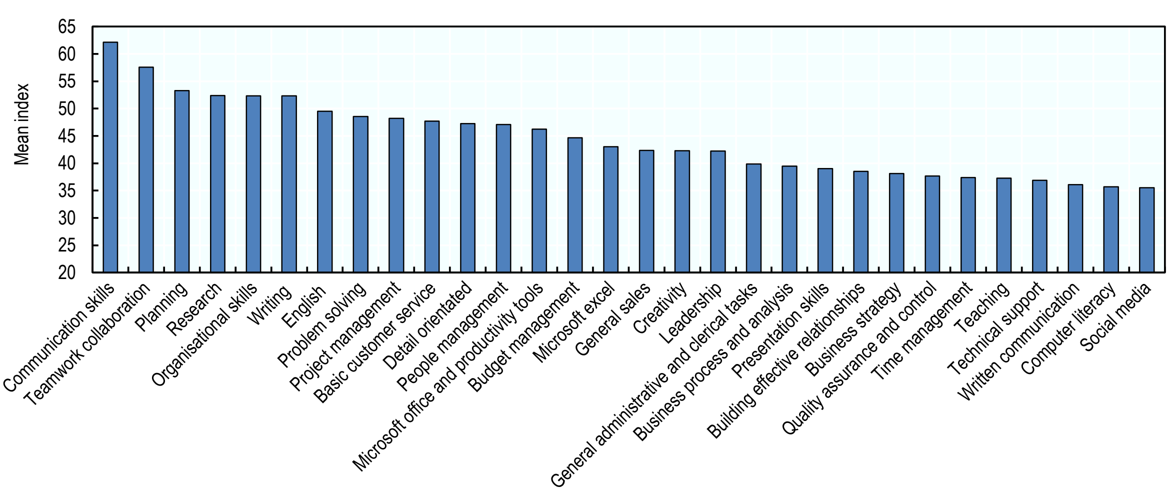
resulting in a vector closer to vec("Paris") than to other word vectors (Mikolov et al., 2013[18]). From a mathematical point of view, this means that if two words share a similar meaning (e.g. Paris and Madrid, which are both country capitals), the cosine of the angle between their vector representations should be close to 1, i.e. an angle close to 0.

A key property of word embeddings and the vector representation of skill keywords in the n-dimensional space is that they allow calculating the number and quality of connections between each skill across the entire set of online vacancies. Being slightly more precise, the connections between a group of keywords can be represented by a mathematical structure called "graph". In such a graph, the skill keywords extracted from online vacancies represent the vertices (also called nodes), which can either be connected when both vertices co-occur in a specific job vacancy or disconnected when both vertices never co-occur in the same vacancy.

In graph theory, "eigenvector centrality" is a measure of the influence of a node in a network. Google developed and uses this measure widely in its PageRank algorithm to quantify the importance of the connections among web pages. This chapter follows the same approach, using the eigenvector centrality index to measure the importance of the connections between skills across millions of job vacancies. Skills that have stronger connections across different occupations and job postings, and therefore high eigenvector centrality, are identified as "transversal".

Figure 5.8. Top 30 transversal skill keywords, by degree of transversality

United Kingdom, 2017-2019



Note: The chart presents the 30 most transversal skills, knowledge areas and technologies emerging from the ML analysis of the text contained in online job postings in the United Kingdom in between 2017 and 2019. Larger bars denote stronger transversality calculated as the eigenvector centrality of each keyword in the corpus of labels collected in online vacancies.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

StatLink https://stat.link/k7j6tv

Figure 5.8 presents the list of the 30 most transversal skills (i.e. those with the highest eigenvector centrality score, see Box 5.1) across online vacancies collected in the United Kingdom in between 2017 and 2019.[5]

The list of top 30 transversal skills is rather heterogeneous, containing soft and technical skills as well as several business-related skills that are shown to be key in many different roles and across various occupations. Amongst the 30 most transversal keywords across online job postings there are communication skills, teamwork collaboration and planning skills. Problem-solving, creativity and relationship-building skills are also highly transversal and important personality traits that are interconnected with a wide variety of vacancies, jobs and tasks in the online postings.

The analysis in Figure 5.8 confirms that a wide variety of jobs today require some knowledge of how to approach and respond to customers effectively or project management skills. Several transversal keywords refer to business-related skills, such as the ability to provide basic customer service, manage a budget (e.g. “budget management”) or provide administrative support. These skills are crucial not only in sales occupations, but also in a much broader set of job descriptions (from plumbers to administrative staff) entailing one-on-one interactions with clients. For instance, among the occupations where basic customer service skills are key, Careerbuilder.com (a well-known website providing career guidance to jobseekers) mentions home health aides, service technicians, housekeepers and even food service workers (CareerBuilder, 2021[19]). Examples of occupations requiring at least basic knowledge of how to interact with clients are, however, virtually countless.

The results in Figure 5.8 also show that digital skill or the ability to operate a digital technology are transversal competencies needed across a wide variety of jobs. This confirms previous results (OECD, 2019[20])) highlighting that digital skills are permeating societies and labour markets not only in high tech occupations, but across virtually all jobs and sectors. Microsoft Office and Productivity tools, Microsoft Excel and computer literacy are among the most transversal digital technologies used in a wide variety of work contexts and tasks. Interestingly, “social media skills” are also highly transversal requirements, reflecting the surging importance of digital platforms in a variety of positions, including business and sales, customer service, management and administration, and financial services (Box 5.2).

Box 5.2. Social media skills: How are these competencies increasingly permeating labour markets?

Social media have grown into a channel for firms of all sizes to communicate with the public. Indeed, brands use their presence on social media accounts to build their reputation, which is ultimately key to their success and growth. A growing number of jobs are therefore incorporating social media-related tasks in their daily routines, and workers must know how to operate them effectively.

In an opinion piece, the leadership consulting firm SpencerStuart (2014[21]) highlights that:

> …social media provides brands with an intimate platform to connect with customers and shape their perceptions, whether through timely and targeted promotions, responsive customer service or the creation of communities of interest. On the other, social media has unquestionably shifted power to the individual, who can tarnish long-established brands with a single angry blog post or quickly coalesce vast numbers of people behind a cause. Organizations’ successes, failures and missteps are now on display as never before.

The empirical evidence on the demand for and use of social media skills is still scarce, but survey data collected by eMarketer in 2014 among US companies with 100 or more employees found that 88% used (or were planning to use) social media platforms to market their products. This does not only mean that marketing managers or social media managers must use social media channels. In fact, the way social media are used in the workplace is fundamentally changing. Reports from Indeed.com (a website publishing job vacancies) stress that social media skills are increasingly required in different occupations and at different levels, from executive assistants to senior vice-presidents.

An analysis of wage and employment returns based on online vacancies

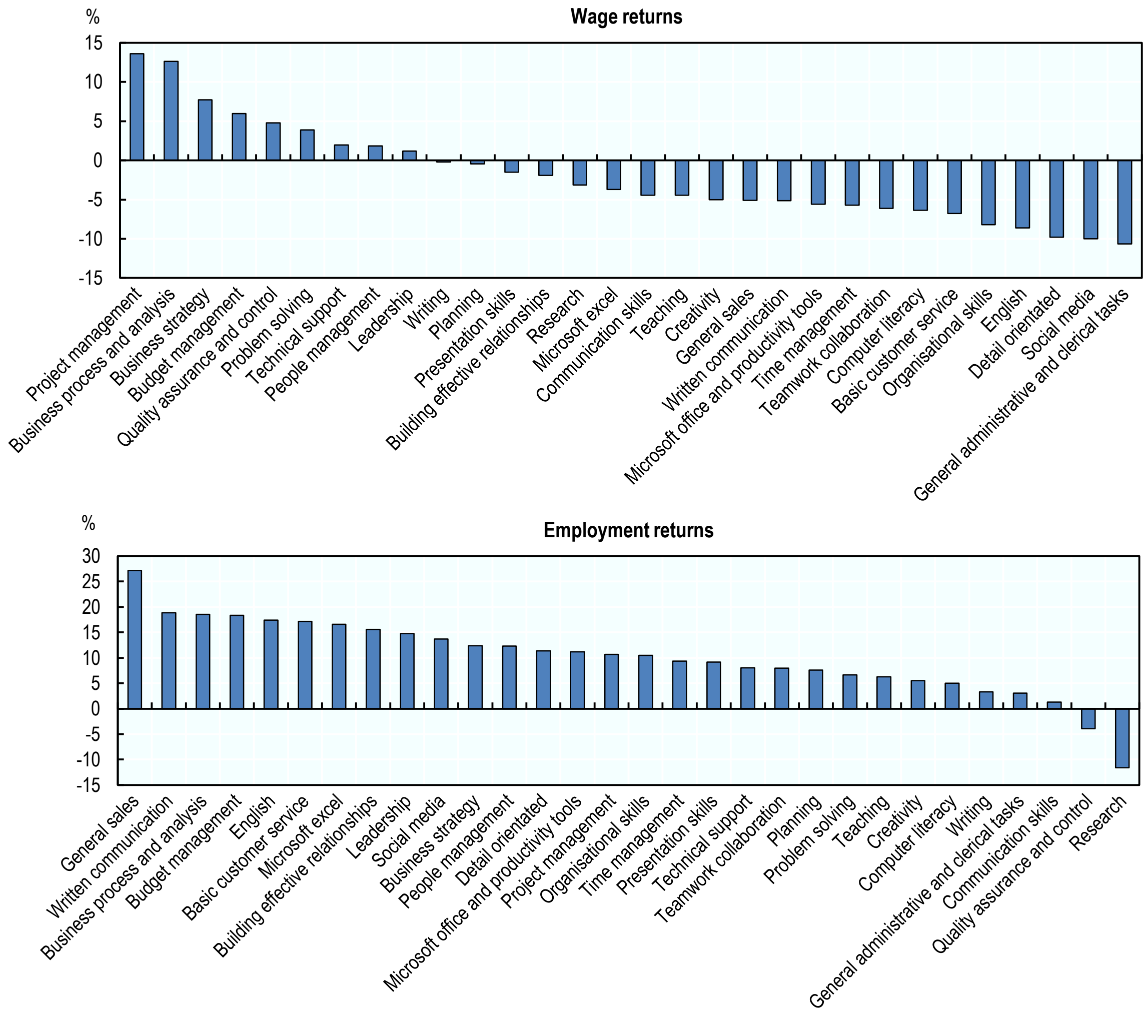
The perceived importance of transversal skills has been growing in the public debate. Reports based on surveys of employers around the world seem to corroborate the idea that transversal skills are in strong demand, and that firms often struggle to find workers with high associated skill levels (Cunningham and Villaseñor, 2016[22]).

Until now, however, empirical evidence has been mixed. Limited data availability has impeded the investigation of the labour-market returns of transversal skills where previous empirical studies have focused on a small set of empirical measures with limited comparability. The advent of large data sets of online vacancies, and the information contained therein, now allow both identifying a large set of transversal skills, and assessing and comparing their wage and employment returns in the labour market.

Figure 5.9 presents the estimated wage and employment returns associated with the top 30 most transversal skills mentioned in online job postings published in the United Kingdom between 2015 and 2019 (details on how the analysis was performed are available in Annex 5.C).

The results show a wide heterogeneity among the labour-market returns (both in terms of wage and employment possibilities) associated with each transversal skill. The transversal skill keywords associated with positive wage and employment returns include knowledge areas such as project management, business process and analysis as well as business strategy and budget management. Project management skills associated with large wage returns usually involve the planning, execution and control of a project, the assessment of the project's risks and opportunities and the management of the resources needed for its completion. Within the project management skills, in recent years the 'agile approaches' have been amongst the most widely used. Agile project management involves breaking a project up into different phases and the engagement of stakeholders and customers in its continuous improvement at every stage. The ability to perform all these tasks (grouped under the label 'project management skills') has become widely required across a variety of different jobs and roles and results from the analysis of online job postings show that this type of skill is associated with an average 14% wage premium and 11% elasticity to job openings. Similarly, knowledge of how to run a business effectively and create a successful strategy (e.g. "business strategy") or to effectively manage budgets rank among those skills that pay off most, both in terms of wage and employment opportunities. Problem solving, people management, leadership and planning are also amongst the transversal skills that are associated with positive and high wage returns, indicating that jobs requiring higher levels of these skills usually pay higher wages. Strong digital skills and the ability to operate digital software like Microsoft Excel or social media are also associated with significant wage returns pointing to the importance of digital skills in supporting individuals' labour market success (see Box 5.3).

Figure 5.9. Wage and employment returns associated with transversal skills



Note: Results are based on separate ordinary least squares (OLS) regressions for each skill keyword that control for average years of education and job-skill complexity, as well as a set of county-level geographical fixed effects and, sector-time and time dummies for the years 2015, 2017 and 2019. All coefficients are statistically significant at 1% level. Coefficients are beta standardised. Results are ordered by the magnitude of the returns in each panel into four groups according to the intensity of the wage and employment returns, and are ranked by the largest wage return in each group. Wage and employment returns indicate the estimated change in wage and job openings associated with a 1 standard deviation increase in the relevance of the skill considered. Positive and larger coefficients indicate that increasingly higher values of the skill are associated with higher wages and more employment opportunities than average.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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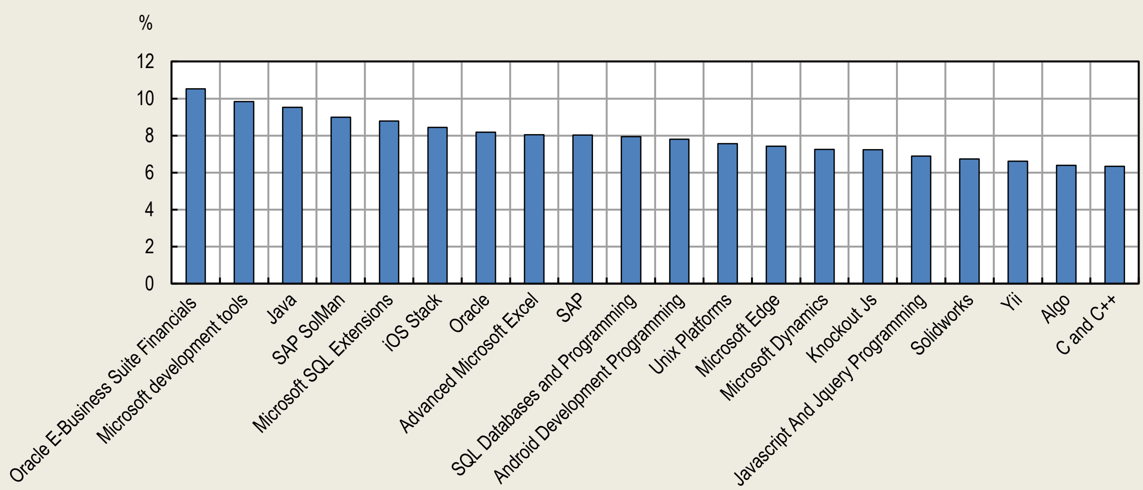
Box 5.3. Developing digital skills: A way to labour market success?

The analysis of online job postings allows to investigate the specific wage returns associated with a wide range of digital skills. Results in Figure 5.10 show that the most widespread digital skills and technologies identified in online job postings are also yielding significant wage returns in the labour market. Among the digital skills leading to the largest wage returns there are Oracle E-business suite financials, Microsoft development tools and Java (a general-purpose programming language for developers). While the demand for specific digital skills is likely to evolve even more rapidly than other demands in the labour market due to the pace of technology progress, results highlight that individuals who are able to keep up with these rapid developments are also able to gain significant wage premium in jobs that are thriving in current labour markets.

Figure 5.10. Top digital skills by wage returns in the United Kingdom

Wage returns of digital skills and technologies, United Kingdom 2015-2019



Note: Results are based on separate ordinary least squares (OLS) regressions for each skill keyword that control for average years of education and job-skill complexity, as well as a set of county-level geographical fixed effect and time dummies for the years 2015, 2017 and 2019. All coefficients are statistically significant at a 1% confidence level. Coefficients are beta standardised. Results are ordered by the magnitude of the returns. Wage returns indicate the estimated change in wage associated with a 1 standard deviation increase in the relevance of the skill considered. Positive and larger coefficients indicate that increasingly higher values of the skill are associated with wages that are above the average in the United Kingdom's labour market for the period in between 2015 and 2019.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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When turning to the association between each transversal skills and the number of job openings, results in Figure 5.9 show that general sales, written communication and business process and analysis are amongst the skill requirements that are associated with the largest employment returns, suggesting that individuals with high levels of those skills are likely to be exposed to a larger number of job openings than on average.

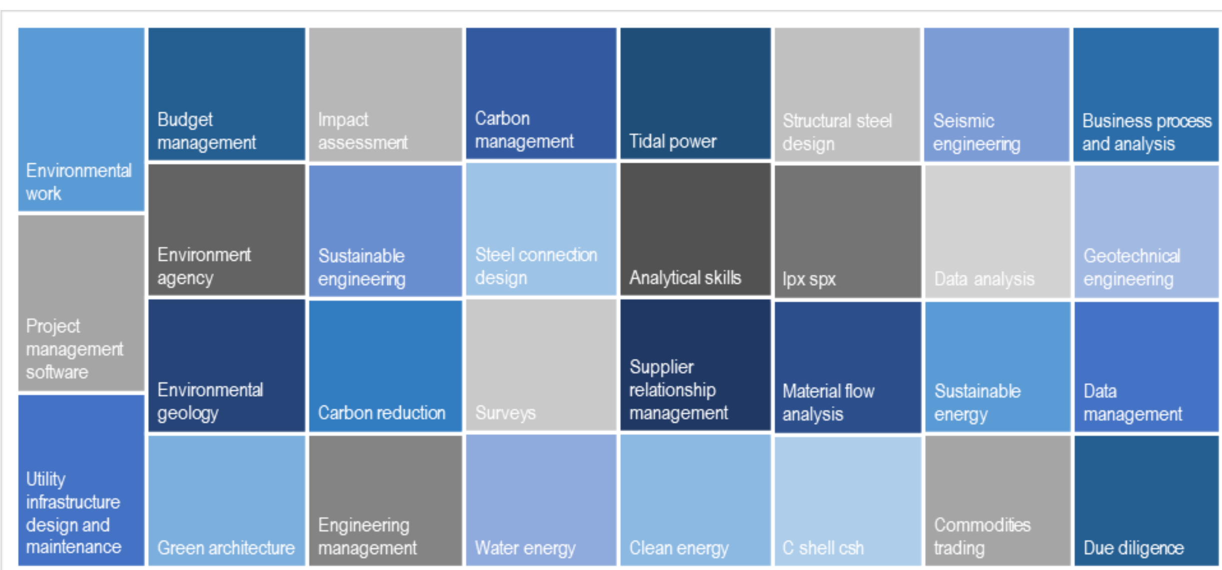
When analysing skill returns, it is important to notice that jobs require a combination of skills to perform tasks, so that each occupation relies on “skill bundles” or skill sets rather than on one single skill. The specific return associated with a particular skill is, therefore, also linked to how this skill is operated in conjunction with other skills and in each particular work context. The analysis of online vacancies reveals that “high-paying” and “low-paying” transversal skills tend to bundle with skills of different nature and that the way skills bundle with each other may be key in defining labour market returns.

Further investigation of the data shows, in fact, that high-paying transversal skills ‘bundle’ (i.e. are usually demanded in conjunction) with technical skills more often than is the case for low-paying transversal skills. In addition, low-paying transversal skills are deployed more frequently in generic occupations (i.e. jobs that do not require high levels of technical and specialised skills), while high-paying transversal skills are more prominent in jobs requiring strong command of technical and highly specialised skills.

Figure 5.11 presents the list of skills that bundle most strongly with project management skills across jobs published on line. The results show that project management skills correlate strongly with only a few other transversal skills (business process and analysis, for instance) while they appear to bundle with a variety of different technical and narrower skills such as the knowledge of utility infrastructure design and maintenance, the knowledge of impact assessment procedures or of engineering management. Interestingly, results suggest that project management skills bundle with several skills in the green economy sector such as the knowledge of environmental work or green architecture and with IT technical skills.[6]

Figure 5.11. Project management skills bundle

United Kingdom, 2015-2019



Note: The figure presents the list of top 30 skills that most strongly bundle together with "Project management skills" across jobs published on line. Results are derived from the correlation of the semantic relevance of each skill with project management skills across occupations, based on the word embedding analysis detailed in Annex 5.C.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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The skills that bundle together with organisational skills are, instead, markedly different from those in the project management skill bundle set. Figure 5.12 shows that, unlike project management skills that mostly bundle with technical skills, organisational skills are usually found in jobs that strongly relate to a large number of other transversal skills, including time management, general administrative and clerical knowledge, and basic customer service skills. This result suggests that jobs requiring high levels of organisational skills tend to bundle in a broader and more transversal skill set, reflecting their "unspecialised" nature.

Figure 5.12. Organisational skills bundle

United Kingdom, 2015-2019

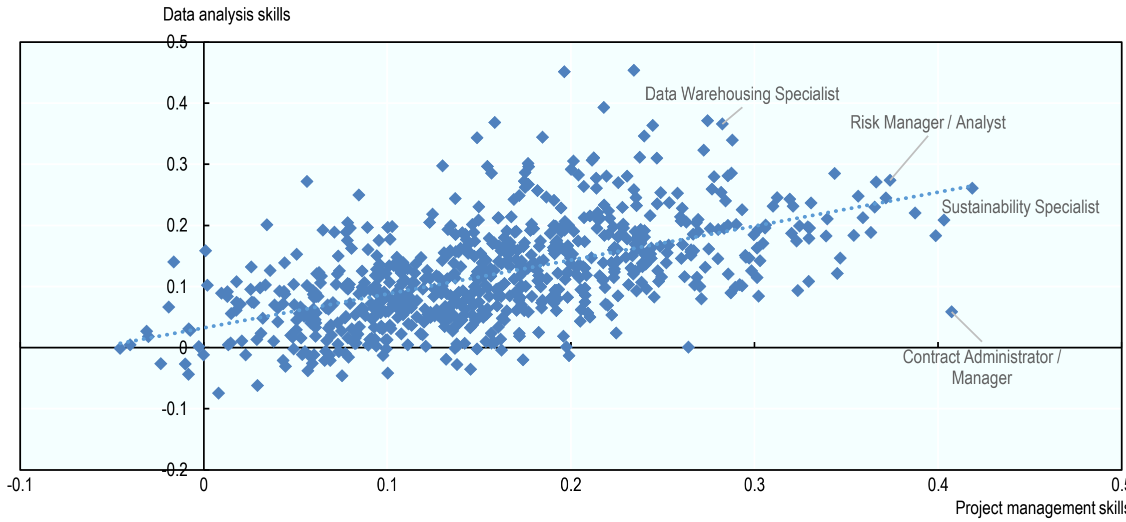
Note: The figure presents the list of top 30 skills that most strongly bundle together with "Organisational skills" across jobs published on line. Results are derived from the correlation of the semantic relevance of each skill with organisational skills across occupations, based on the word embedding analysis detailed in Annex 5.C.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

StatLink https://stat.link/ayjnzh

Results also suggest that the returns associated with transversal skills crucially depend on the work context and job in which they are used intensively. For instance, job profiles that are generally in high demand such as Risk manager analysts, Sustainability specialists or Data warehousing specialists are also occupations that rely intensively on project management or data analysis skills (Figure 5.13). Conversely, Figure 5.14 shows that organisational and communication skills are relevant in a much more diverse group of jobs, including family therapists, veterinary nurses and assistants– some of which pay low wages. Organisational and communication skills are, instead, less relevant in technical and high-paying jobs, such as mobile application developers, computer systems engineers or business intelligence architects, reflecting the overall lower returns associated to those skills.

Figure 5.13. Correlations between project management and data analysis skills by occupation

United Kingdom, 2015-2019



Note: The dots in the chart represent occupations whose values indicate the relevance of the relationship between the skills and the occupations. Higher values indicate a smaller distance (higher relevance) between the skill and the occupation vector representations. The results on the relevance of each skill for the occupation are derived from the analysis of the corpus of online vacancies for the United Kingdom in between 2015 and 2019, transforming textual information contained in online job postings into mathematical vectors using NLP algorithms (see details in Annex 5.C).
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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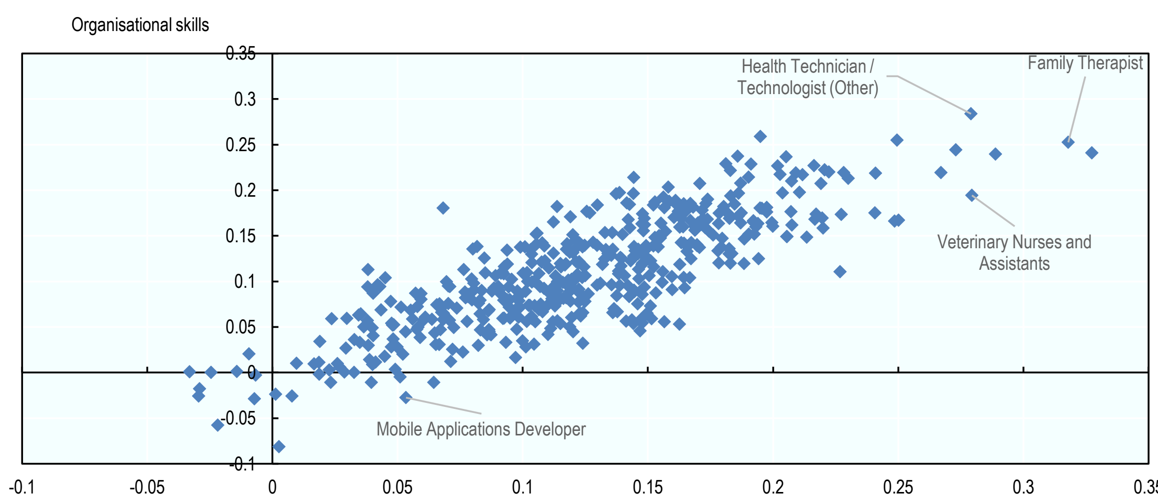
Figure 5.14. Correlations between organisational and communication skills by occupation

United Kingdom, 2015-2019



Note: The dots in the chart represent occupations whose values indicate the relevance of the relationship between the skills and the occupations. Higher values indicate a smaller distance (higher relevance) between the skill and the occupation vector representations. The results on the relevance of each skill for the occupation are derived from the analysis of the corpus of online vacancies for the United Kingdom in between 2015 and 2019, transforming textual information contained in online job postings into mathematical vectors using NLP algorithms (see details in Annex 5.C).
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

StatLink https://stat.link/xlivqs

Box 5.4. Communication skills: A buzzword or true demand?

Although the results in Figure 5.9 show that communication skills are associated with negative wage returns, caveats to the interpretation of these results should be considered. This result may seem puzzling at first glance, as the common narrative has stressed their importance in the labour market. Several reasons may explain the disconnect between widely reported claims about the key importance of communication skills in the labour market and the mixed empirical observations that apparently contradict this narrative. On the one hand, the analysis of online vacancies for the United Kingdom confirms that “communication skills” is by far the most common keyword in the collected data, appearing more than 1.6 million times (approximately 4% of total skill mentions – double the frequency of the second most popular skill, “basic customer service”). However, such an abundance creates measurement problems, as the inference based on this information is likely to suffer from considerable noise owing to the limited variance across occupations. In practice, if (almost) all job postings mention communication skills, those words become a noisy and imprecise indicator of the terms to which they refer. This, in turn, makes it difficult to disentangle the returns associated with communication skills.

Along these lines, Monster.com, one of the most important webpages aggregating curricula vitae (CVs) and online vacancies, recently listed “communication skills” among those “buzzwords” job seekers should avoid in their CVs, along with “hard worker” or “creative”. This is because they have become catchwords that convey little information about the candidate, the job or the tasks. Instead, curators at Monster.com suggest that candidates provide much more specific information in their resumes or CVs, describing in tangible ways how – and in what context – they have developed precise skills linked to communication or creativity. Similarly, employers looking for candidates who are able to communicate effectively should detail in their advertisements the types of communication channels or methods they expect the candidate to deploy in the job.

How can governments spur the development of transversal skills?

The results presented in previous sections show that transversal skills span a wide range of multidimensional skills, from the ability to operate digital technologies to more personal traits that are often embedded in an individual’s personality - see also Whittemore (2018[23]). Several transversal skills are shown to enjoy positive and large returns in the labour market, and should therefore be at the core of lifelong learning systems. The key question, however, is how to best support their development. As the majority of transversal skills are not tied to any particular subject and are developed in all areas of study, innovative approaches to developing transversal skills tend to eschew input-led, subject-oriented approaches, focusing instead increasingly on specific learning outcomes. Acquiring transversal skills requires interactive and active learning. Constructivist learning theories suggest that learning through authentic activities, as opposed to solely through instruction, helps develop key competencies (Terzieva and Traina, 2015[24]).

Spurring such involvement can be challenging, but educational programmes at all levels should consider – and wherever possible, reflect real-life applications. For instance, collaborative learning (e.g. project-based and problem-based learning approaches) allows learners to work together in small groups to achieve a common objective, and can facilitate the simultaneous development of several transversal skills. Interactive learning environments encourage learners to be active and autonomous while also collaborating with other learners and developing social and communicative competencies (Terzieva and Traina, 2015[24]).

Training based on real-world contexts and work-based learning has also been shown to motivate learners more than traditional approaches (Lepper and Henderlong, 2000[25]; Garris, Ahlers and Driskell, 2002[26]) helping learners remember more easily concepts they discover on their own (De Jong and Van Joolingen, 1998[27]) and potentially leading them to develop many of the transversal traits permeating job listings. Hence, non-formal and informal learning are therefore key channels for acquiring transversal skills, as they are usually undertaken in a work context to address real-life issues.

"Learning to learn" can help individuals at all stages of the life cycle adapt to changing social, economic and technological landscapes. Allowing learning to be more self-directed can bolster an individual's ability to learn independently. Self-directed and flexible digital learning tools, such as micro-credentials, tutorials and web-based courses, allow individuals to learn at their own speed and become involved in topics of their choosing where they see real-life implications. This can encourage a more self-aware learning process, equipping learners with skills they can apply transversally across various contexts.

Such a varied approach to the development of transversal skills comes with a set of important challenges. To start with, education models today remain largely focused on settings where learners tend to assume a receptive position (Whittemore, 2018[23]), teachers are trained in narrow subjects, and school schedules are organised around single subject lessons. This setting does not promote cross-fertilisation among different areas and subjects, possibly hindering the development of transversal skills at school. As high-quality teaching is key to nurturing transversal skills and competencies, higher education systems should help teachers adapt continuously to changing curricula.

Along with more traditional settings, countries should consider promoting learning environments that are not classroom-based. Interactive methods are increasingly technology-enhanced, allowing the use of innovative tools such as virtual or augmented reality. Similarly, transversal skills can be developed in an applied context, through placements, internships and study programmes (Terzieva and Traina, 2015[24]).

Another important aspect to consider is that transversal skills should not solely permeate the training curriculum of formal initial education, nor should such training focus solely on children and young people. People of all ages should continue to develop their transversal competencies, since the world of work increasingly requires a range of transversal skills and innovative learning approaches are spread throughout an individual's life course.

Looking into the future of labour-market and skill demands

Before the COVID-19 pandemic precipitated world economies into a crisis of unprecedented magnitude, technological change, automation and digitalisation, as well as the advent of artificial intelligence and big data, were already reshaping societies and the world of work at a breakneck speed. Updated OECD estimates project that up to 15% of existing jobs would disappear because of automation over the next 15-20 years, and that another 32% would undergo radical changes because some of the tasks originally performed by workers would be automated through new software and robots (OECD, 2019[28]). At the same time, estimates revealed long-term increases in employment rates in most OECD countries and new job creation through technology (PwC, 2018[29]; OECD, 2019[28]; World Economic Forum, 2020[8]). Since job creation and job destruction occur for different categories of workers, however, the distributional implications of technology can be profound. Some groups, such as low-skilled or older workers, are especially vulnerable to technological disruption and are ill-equipped to harness the benefits of technological change. Against this backdrop, governments are mobilising to prevent widening disparities in labour-market performance according to an individual's age, gender and socio-economic background.

Estimates on the risk of automation suggest that even if changes in labour markets owing to COVID-19 were to be short-lived, labour markets are still poised to change dramatically in the medium and long term. Many argue that some of the changes implemented as a result of the COVID-19 crisis will remain or even accelerate (World Economic Forum, 2020[8]), interacting with technological innovations to produce even more substantial and rapid disruptions. In the aftermath of the pandemic, many workers who will be able to resume their jobs may still experience significant changes. Other workers may not be able to re-enter the labour market in their previous roles, and will need to retrain and upskill to find a new job. Here again, targeted and responsive lifelong learning is key to help individuals navigate this uncertain and challenging landscape.

The remainder of this section looks at the short- and medium-term outlook for labour markets. It analyses and compares the skill profiles of jobs that are projected to decline with the skill profiles of jobs that are expected to grow as a result of structural changes in the economy, automation and digitalisation. It also compares jobs that have been hit hard during the pandemic with jobs that have experienced a surge in demand. The section mines the granular information contained in online vacancies to depict precise retraining pathways that would help workers in declining occupations transition to high-quality, growing jobs that will enable them to thrive in future labour markets.

Fastest-declining and growing occupations, skill profiles and retraining pathways

Predicting the future is a challenging task. To put things into perspective, scrolling through Instagram on a mobile phone, watching a movie on Netflix or answering emails on an iPad was impossible just over a decade ago, as those technologies and platforms had not yet been invented. The technology behind 4G connections, used nowadays in virtually all mobile phones, was not yet available. Some of the largest players in the platform economy, like Uber or Airbnb, were barely more than prototypes in some countries. Similarly, online streaming platforms like Netflix or Spotify have only emerged in the last decade, and virtually all the video-conferencing technologies that have been heavily used during the COVID-19 pandemic to allow remote working did not exist.

Although it is impossible to pinpoint which technologies will be developed in the next ten years and their future impact on the lives of millions of citizens, some trends are clear. For example, when executives around the globe were surveyed to get a sense of their short- to medium-term business plans and how these would be affected by technological progress, the vast majority (84%) indicated they intended to accelerate the digitalisation of their work processes and deploy new technologies (World Economic Forum, 2020[8]). These plans also involved expanding remote work. Approximately half of employers also reported they had plans to accelerate automation in their companies. Some 43% of the businesses surveyed believed that new technologies would reduce their workforce, but another 34% expected technologies to increase the demand for qualified labour. Despite anxieties around potential job losses owing to automation and digitalisation, most studies in this area (PwC, 2018[29]; OECD, 2019[28]; World Economic Forum, 2020[8]) seem to agree that the net impact of technology on job creation will be positive, but that the distribution of gains and losses among workers in different occupations, sectors and different skill sets will be uneven. The U.S. Bureau of Labor Statistics (BLS) developed granular predictions of the impact of megatrends and structural changes on the labour market, looking at the expected impact on employment by occupation (see Box 5.5).

Box 5.5. Projections of fast growing and declining occupations

The U.S. BLS regularly publishes the National Employment Matrix which develops projected-year employment data for wage and salary jobs, including all agricultural workers and workers employed by private households. The matrix uses a conceptual framework that divides industry employment between occupations, based on expected structural changes in demand and occupations within a given industry. To project these changes in occupational demand, BLS economists examine qualitative sources such as scholarly articles, expert interviews and news stories, as well as quantitative resources such as historical data and externally produced projections. These reviews identify structural transformations in the economy that are expected to change an occupation's share of industry employment. Projected-year employment data for self-employed workers are developed similarly, but at a less-detailed level than wage and salary employment.

Source: U.S. Bureau of Labor Statistics (2020[30]), Occupational Employment Statistics Program,, https://www.bls.gov/emp/data/occupational-data.htm.

Table 5.1 ranks occupations that are projected to decline the fastest between 2019 and 2029 in the United States.[7] Word processors and typists, along with parking enforcement workers, are among the occupations that will experience the sharpest decline (over 35%) relative to their employment level in 2019. Occupations such as travel agents are projected to decline by 26%, and postmasters and mail superintendents by 22%, along with positions in very distant sectors, such as nuclear power reactor operators (-36%) and electronic equipment installers and repairers for motor vehicles (-23%). The results indicate that technological change is affecting jobs entailing different skill sets and tasks in virtually all sectors.

Some of the jobs at high risk of disruption employ a relatively small share of the total workforce (only 50 000 people worked as word processors and typists in the Unites States in 2019), while others employ many workers across different sectors of the economy (around 500 000 people worked as executive secretaries and executive administrative assistants in 2019).

Table 5.1. Fastest declining occupations in the United States, 2019 and projected 2029

2019 National Employment Matrix title and code	Employment		Change, 2019-29		Median annual wage, 2019
	2019	2029	Number	Percent	
Total, all occupations	*162 795.6*	*168 834.7*	*6 039.2*	*3.7*	*39 810*
Word processors and typists	52.7	33.5	-19.2	-36.4	40 340
Parking enforcement workers	8.1	5.2	-2.9	-36.2	40 920
Nuclear power reactor operators	5.3	3.4	-1.9	-35.7	100 530
Watch and clock repairers	3.2	2.1	-1	-32.3	42 520
Cutters and trimmers, hand	9.8	6.9	-2.9	-29.9	30 200
Telephone operators	5	3.6	-1.4	-27.9	35 750
Travel agents	82	60.8	-21.3	-25.9	40 660
Data-entry keyers	172.4	130	-42.4	-24.6	33 490
Electronic equipment installers and repairers, motor vehicles	10.4	8	-2.4	-23.2	37 380
Switchboard operators, including answering service	69.9	54.1	-15.7	-22.5	30 610
Manufactured building and mobile home installers	2.9	2.2	-0.6	-22.3	33 890
Timing device assemblers and adjusters	1.3	1	-0.3	-22.3	35 080

2019 National Employment Matrix title and code	Employment		Change, 2019-29		Median annual wage, 2019
	2019	2029	Number	Percent	
Legal secretaries and administrative assistants	171.8	133.8	-38	-22.1	47 300
Postmasters and mail superintendents	13.4	10.5	-2.9	-21.9	76 900
Forging machine setters, operators, and tenders, metal and plastic	16.4	13	-3.5	-21.1	39 670
Prepress technicians and workers	30.2	24	-6.3	-20.7	40 510
Executive secretaries and executive administrative assistants	593.4	472.4	-121.1	-20.4	60 890
Floral designers	51.8	41.4	-10.4	-20.1	28 040
Door-to-door sales workers, news and street vendors, and related workers	72.9	58.3	-14.6	-20	27 420
Grinding and polishing workers, hand	29	23.4	-5.6	-19.5	30 600
Photographic process workers and processing machine operators	12.3	9.9	-2.4	-19.4	32 280
Refractory materials repairers, except brick masons	0.8	0.7	-0.2	-19.3	53 990
Desktop publishers	10.4	8.4	-2	-19	45 390
Drilling and boring machine tool setters, operators and tenders, metal and plastic	11.2	9.1	-2.1	-19	38 910
Nuclear technicians	6.7	5.4	-1.3	-18.9	82 080
Pressers, textile, garment and related materials	38.3	31.1	-7.2	-18.9	24 190
Coil winders, tapers, and finishers	13	10.5	-2.4	-18.7	36 520
Milling and planing machine-setters, operators and tenders, metal and plastic	19.2	15.6	-3.6	-18.6	43 210
Postal service mail sorters, processors and processing-machine operators	98.5	80.9	-17.6	-17.8	60 140
Aircraft structure, surfaces, rigging and systems assemblers	43.9	36.3	-7.6	-17.4	54 210
Average for fast-declining occupations	**1 656.2**	**1 295.5**	**-360.7**	**-22%**	**44 121**

Note: Employment figures are expressed in thousands. Data are ranked by sharpest projected decline. Wage data cover non-farm wage and salary workers. They do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
Source: Employment Projections program, U.S. BLS and OECD calculations.

StatLink https://stat.link/5xcbty

The information contained in the online vacancies collected in the United States provides important and unprecedently granular information on the most relevant skills and knowledge used by individuals in different occupations, as well as the tasks and technologies that characterise employment in each occupation, including those at a high risk of disruption. The results in Figure 5.15 show the skill bundles of word processors and typists (the occupation with the strongest projected decline between 2019 and 2029), and executive secretaries and executive administrative assistants (the largest occupation in employment size among those with the strongest projected decline between 2019 and 2029).

Word processors and typists use a wide array of skills at different levels and perform tasks in various technical knowledge areas. For instance, the results in Figure 5.15 indicate that word processors and typists are usually required to produce technical material, prepare statistical reports, plan and type statistical tables, and combine and rearrange material from different sources and require basic knowledge of trading,[8] transaction processing, billing and legal document processing and revision.

The analysis of online vacancies also indicates that word processors and typists are required to operate a range of different technologies. Among these, Adobe PostScript is an important tool (especially in electronic publishing and desktop publishing) which was introduced in 1984, but quickly became the standard allowing proprietary systems to overcome incompatibilities between computers and printing systems. Another important tool is Sugar CRM, whose functionality includes salesforce automation, marketing campaigns, customer support and collaboration.

On a typical day of work, word processors and typists also perform a variety of more routine tasks, ranging from operating office machines; filing and storing completed documents on computer hard drives; and maintaining a computer filing system to store, retrieve, update and delete documents. They must also gather, register and arrange the material to be typed, as well as keep records of work performed and transmit work electronically to other locations (also known as lockbox processing).

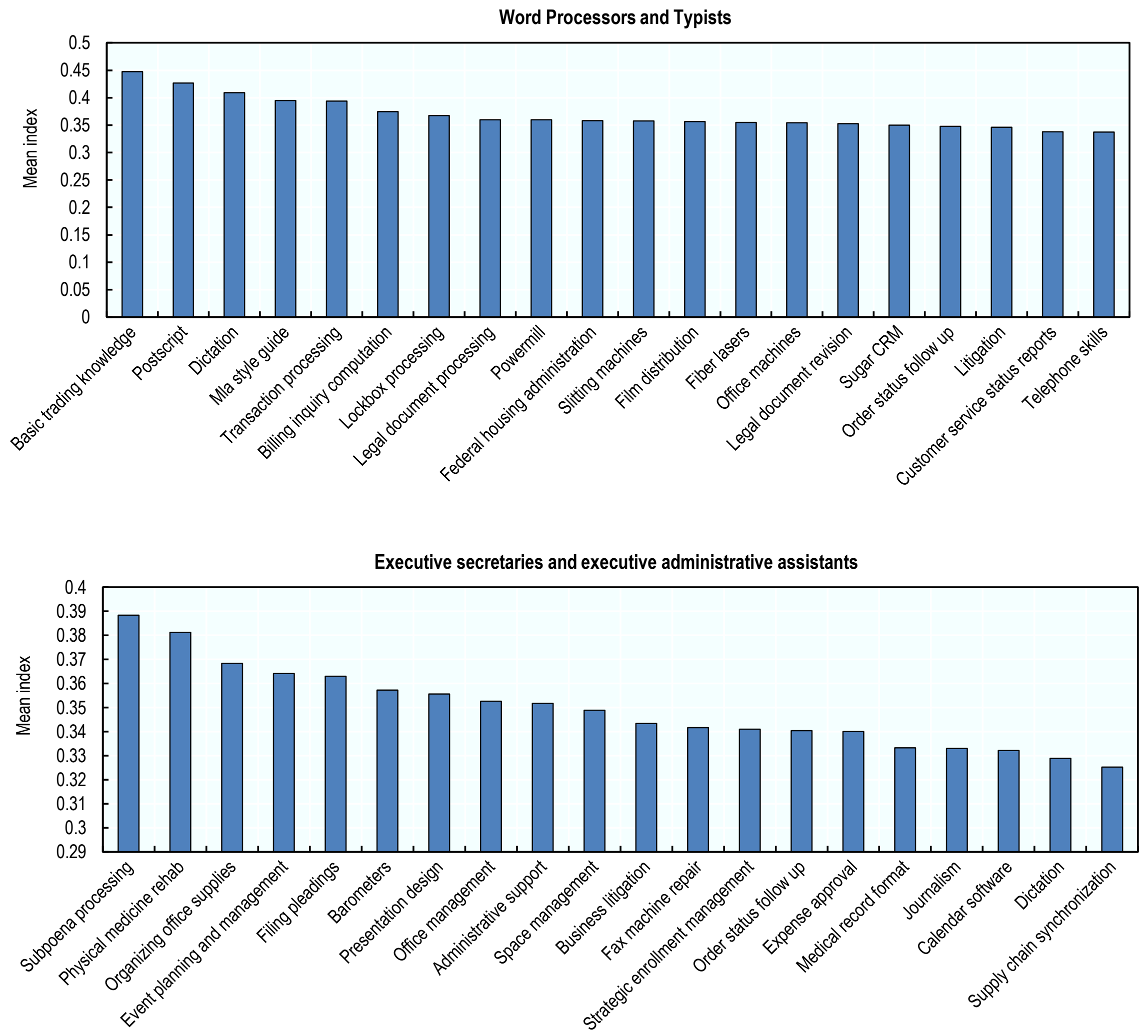
Some of these tasks face a high risk of automation. For instance, the analysis of online vacancies in the United States shows that word processors and typists are still required to take notes from dictation, operate office machines and have telephone skills. New technologies, however, will soon make those tasks and skills obsolete. 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. The new Microsoft Windows operating system comes with Windows Speech Recognition, a free program that lets users control their computer and convert speech into text, and the number of similar applications (both for mobile phones and desktop computers) has increased exponentially in recent years. 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. These new technologies, however, will make many of the old tasks performed by word processors and typists redundant, very likely leading to a sharp decrease in demand.

Executive secretaries and executive administrative assistant positions are projected to decline by more than 20% in the coming decade. In the United States alone, approximately 120 000 of those jobs will be lost to technological change and structural trends, and the tasks and skill requirements of many more jobs may change substantially. As of today, information contained in online vacancies indicates that executive secretaries and executive administrative assistants combine different skills and knowledge in a variety of routine but also complex tasks. Among their higher-level tasks are knowledge of legal and/or health aspects (interagency security committee standard, subpoena processing and physical medicine rehab), which are commonly required to write technical minutes of meetings for executive managers in those fields. Typically, executive secretaries and executive administrative assistants should also be able to manage event planning, perform order status follow up and expense approval, and often file pleadings.

Executive secretaries and executive administrative assistants also perform many routine tasks that are poised to disappear or change dramatically in the near future, ranging from using calendar software to organising office supplies and even supervising the repair of fax machines. For instance, new software programs functionalities built into some of the most popular email providers (such as Gmail) already detect dates and meeting requests in emails, and schedule the calendars accordingly. Such programs also notify the user if the email contains questions or requests that have remained unanswered for more than five days.

Figure 5.15. Skill profiles of projected fast-declining occupations (selection)

Top 20 most relevant skills per occupation in the United States, 2016 to 2018



Note: Skills are ranked according to their relevance for the occupation, approximated by the semantic similarity (ranging from 1- to 1) between each skill and the lexicon used across all job postings collected for the occupation under examination. The analysis covers approximately 62 million job vacancies collected in the United States for the years 2016, 2017 and 2018. Details on the methodology can be found in Annex 5.B.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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Automation and technological change will inevitably make some tasks and skills increasingly redundant – but they will also free workers' time to perform more productive activities in the same jobs or new kinds of jobs. New occupations will probably emerge in response to technological change, reshuffling skills and tasks in innovative ways. Surveys of employers (World Economic Forum, 2020[8]) indicate that "increasingly redundant roles will decline from being 15.4% of the workforce to 9% (6.4% decline), and that emerging professions will grow from 7.8% to 13.5% (5.7% growth) of the total employee base of company respondents" by 2025.

According to U.S. BLS projections, employment in a wide range of jobs is expected to grow (Table 5.2), particularly among at least three main occupational categories. Occupations in the energy sector, many of which are related directly to the introduction of “green” technologies like wind turbine service technicians or solar photovoltaic installers, are set to grow by more than 50% by 2029 compared to 2019. Other jobs and tasks in the same sector are also becoming “greener”, including derrick operators, rotary drill operators and roustabouts (oil and gas), which are projected to grow by at least 25% by 2029.[9]

Employment in the healthcare sector should also increase dramatically in the next decade. Positions such as home health and personal care aides, physical therapist assistants, and medical and health services managers should grow by more than 30%, and nurse practitioners by 52%. Although these changes partly reflect the unique features of the US healthcare system, population ageing and the growing number of individuals suffering from chronic diseases are likely to spur similar changes in other countries.

Employment in the tech and data-analysis sector is also projected to grow significantly, thanks to exponential growth in data availability for commercial, research and business use. Occupations such as statisticians, information security analysts, data scientists and mathematical science occupations, software developers, and software quality-assurance analysts and testers should grow by 20-30% over the next decade. The top 30 occupations that are projected to grow the fastest will expand by 28% on average by 2029, creating more than 2.5 million new job opportunities and resulting in nearly 12 million jobs in the United States alone.

Table 5.2. Fastest-growing occupations, 2019 and projected 2029

United States

2019 National Employment Matrix title and code	Employment		Change, 2019-29		Median annual wage, 2019, USD
	2019	2029	Number	Percent	
Total, all occupations	162 795.6	168 834.7	6 039.2	3.7	39 810
Wind turbine service technicians	7	11.3	4.3	60.7	52 910
Nurse practitioners	211.3	322	110.7	52.4	109 820
Solar photovoltaic installers	12	18.1	6.1	50.5	44 890
Occupational therapy assistants	47.1	63.5	16.3	34.6	61 510
Statisticians	42.7	57.5	14.8	34.6	91 160
Home health and personal care aides	3 439.7	4 599.2	1 159.5	33.7	25 280
Physical therapist assistants	98.7	130.9	32.2	32.6	58 790
Medical and health services managers	422.3	555.5	133.2	31.5	100 980
Physician assistants	125.5	164.8	39.3	31.3	112 260
Information security analysts	131	171.9	40.9	31.2	99 730
Data scientists and mathematical science occupations, all other	33.2	43.4	10.3	30.9	94 280
Derrick operators, oil and gas	12	15.7	3.7	30.5	46 990
Rotary drill operators, oil and gas	20.9	26.6	5.6	26.9	54 980
Roustabouts, oil and gas	58.5	73.1	14.7	25.1	38 910
Speech-language pathologists	162.6	203.1	40.5	24.9	79 120
Operations research analysts	105.1	131.3	26.1	24.8	84 810
Substance abuse, behavioural disorder and mental health counsellors	319.4	398.4	79	24.7	46 240
Forest fire inspectors and prevention specialists	2.3	2.8	0.5	24.3	45 270
Cooks, restaurant	1 417.3	1 744.6	327.3	23.1	27 790
Animal caretakers	300.7	369.5	68.8	22.9	24 780
Service unit operators, oil and gas	51.7	63.6	11.8	22.9	46 740
Marriage and family therapists	66.2	80.9	14.8	22.3	49 610

2019 National Employment Matrix title and code	Employment		Change, 2019-29		Median annual wage, 2019, USD
	2019	2029	Number	Percent	
Computer numerically controlled tool programmers	25.7	31.3	5.6	21.9	56 450
Film and video editors	38.3	46.5	8.3	21.6	63 780
Software developers and software quality-assurance analysts and testers	1 469.2	1 785.2	316	21.5	107 510
Genetic counsellors	2.6	3.2	0.6	21.5	81 880
Physical therapist aides	50.6	61.3	10.8	21.3	27 000
Massage therapists	166.7	201.1	34.4	20.6	42 820
Health specialties teachers, post-secondary	254	306.1	52.1	20.5	97 320
Helpers -- extraction workers	16.9	20.3	3.4	20.2	37 120
Average for fast-growing occupations	**9 111.2**	**11 702.7**	**2 591.5**	**28%**	**63 691**

Note: Employment figures are expressed in thousands. Data are ranked by sharpest projected increase. Wage data cover non-farm wage and salary workers; they do not cover the self-employed, owners and partners in unincorporated firms, or household workers. USD= US dollars.
Source: Occupational Employment Statistics program, U.S. BLS and OECD calculations.

StatLink https://stat.link/bg17ek

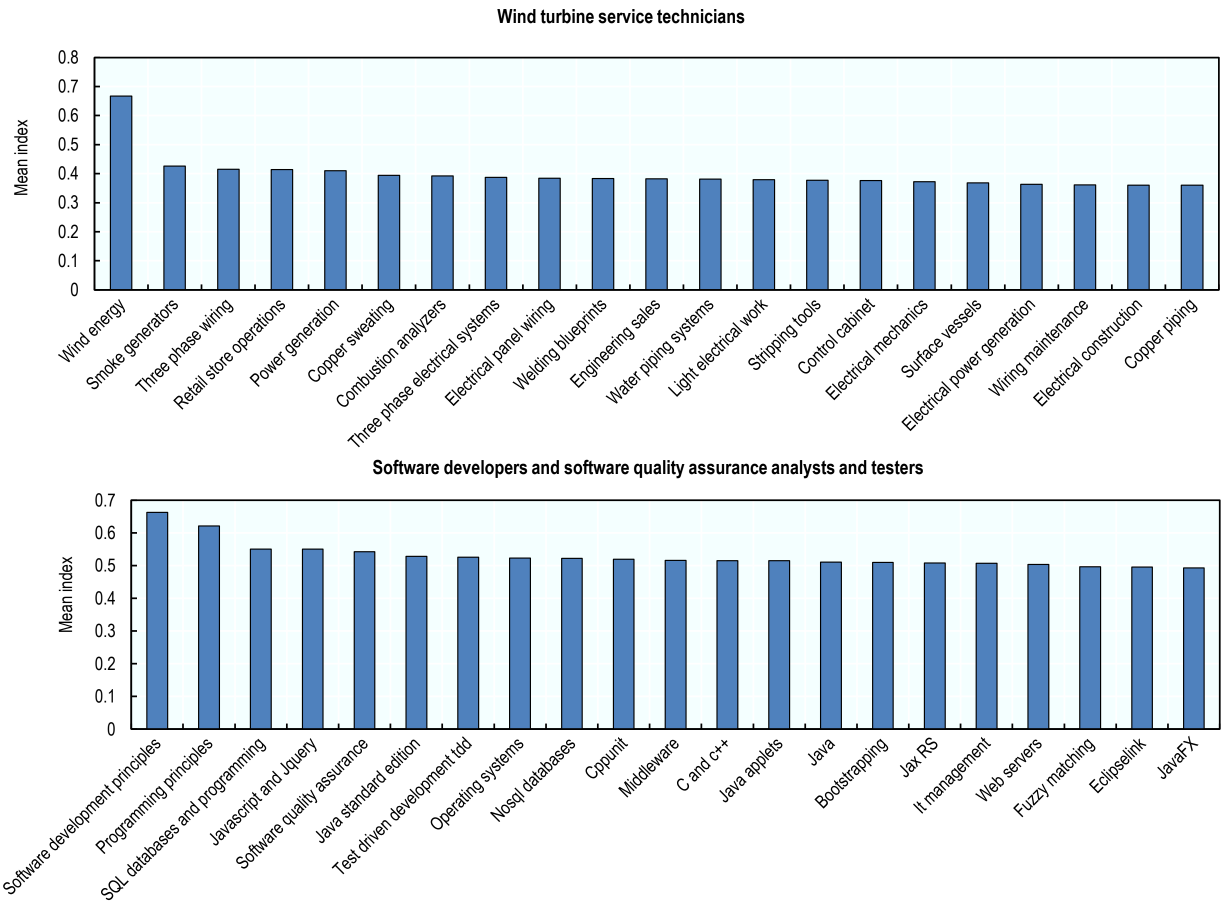
The analysis of online vacancies allows collecting granular insights about the skills and knowledge areas that are most relevant to growing occupations, as well as the tasks typically performed in these occupations. The results in Figure 5.16 emerging from the analysis of online vacancies collected between 2016 and 2018 in the United States show the skill bundle associated with wind turbine service technicians. Wind turbine service technicians are usually tasked to install, inspect, maintain, operate and repair wind turbines as well as to diagnose and fix any problem that could cause the turbine to shut down unexpectedly. Knowledge of wind energy is therefore a prerequisite for this occupation, but additional technical skills and knowledge areas are also necessary to perform this job successfully and are therefore required in related job vacancies.

For instance, wind turbine service technicians collect turbine data for testing and analysis, using smoke generators (designed to facilitate the observation of air movements and air tracing in many types of airflow situations) or operating combustion analysers. Many of the tasks associated with this job also consist in maintaining and testing electrical components, and mechanical and hydraulic systems. Knowledge of three-phase wiring and electrical systems (common tools that alternate electric power generation, transmission and distribution) are key for this occupation and highly relevant across job postings, along with copper sweating skills, knowledge of water piping systems, and the ability to read and produce welding blueprints. Interestingly, online vacancies also reveal that wind turbine service technicians are expected to be familiar with retail store operations (e.g. inventory oversight and customer service), as well as promote products, and provide technical advice and support to customers (engineering sales skills).

Software developers, and software quality-assurance analysts and testers, are job profiles that are projected to grow substantially (21%) by 2029. Those occupations require knowledge of software development principles and programming principles, SQL databases and programming, Java (a general-purpose programming language for developers) and JQuery (a free open-source JavaScript software library used by 73% of the 10 million most popular websites and designed to simplify HTML manipulation, event handling, cascading style sheets animations and Ajax). The results of the textual analysis of online vacancies indicate clearly that knowledge of programming languages (i.e. C and C++, Eclipselink and various Java applications, such as JavaFX or JavaRS) represents the lion's share of the most relevant skills for software developers and software quality-assurance analysts. However, other statistical skills, such as bootstrapping (i.e. tests or metrics using random sampling) and fuzzy matching (a technique that allows matching data records that are not 100% similar) are also key (e.g. in big-data analyses).

Figure 5.16. Skill profiles of projected fast-growing occupations (selection)

Top 20 most relevant skills per occupation in the United States, 2016 to 2018



Note: Skills are ranked according to their relevance for the occupation, approximated by the semantic similarity (ranging from 1- to 1) between each skill and the lexicon used across all job postings collected for the occupation under examination. The analysis covers approximately 62 million job vacancies collected in the United States for the years 2016, 2017 and 2018. Details on the methodology can be found in Annex 5.B.

Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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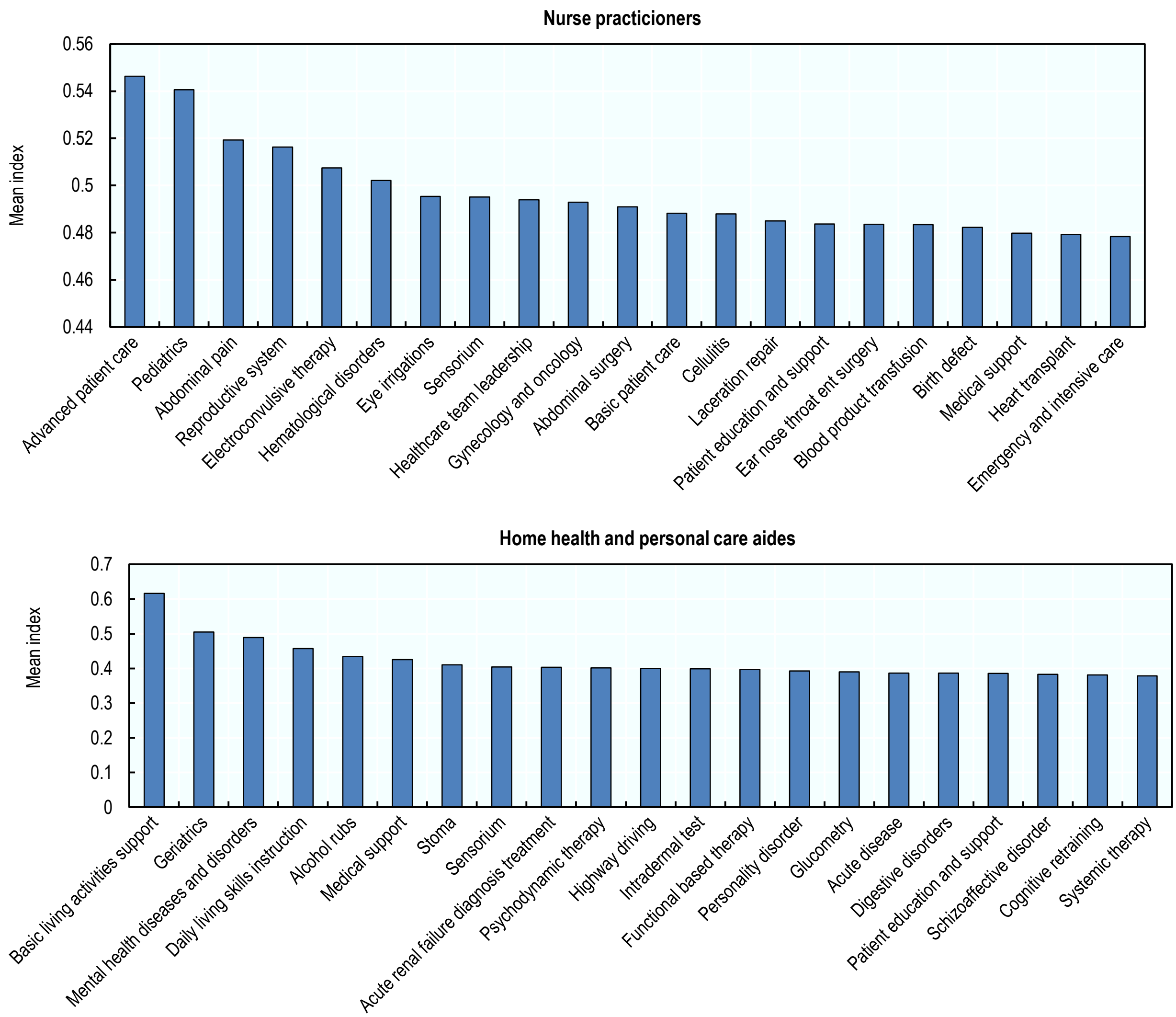
Figure 5.17. Fast-growing healthcare occupations - skill bundles

Top 20 most relevant skills in each occupation - United States, 2016 to 2018



Note: Skills are ranked according to their relevance for the occupation, approximated by the semantic similarity (ranging from 1- to 1) between each skill and the lexicon used across all job postings collected for the occupation under examination. The analysis covers approximately 62 million job vacancies collected in the United States for the years 2016, 2017 and 2018. Details on the methodology can be found in Annex 5.B.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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A growing healthcare sector: Evidence on skill bundles from online vacancies

Occupations in the healthcare sector represent 13 of the 30 occupations that are projected to grow the fastest by 2029 and as such, deserve special attention. In the United States, for instance, employment for nurse practitioners is expected to double by 2029, up to 300 000 jobs. Nurse practitioners are skilled clinicians who blend clinical expertise in diagnosing and treating health conditions, with an additional emphasis on disease prevention and health management. They are trained to assess patient needs, order and interpret diagnostic and laboratory tests, diagnose diseases, and formulate and prescribe treatment plans. According to the BLS, a nurse practitioner earns a median annual wage of more than USD 100 000, more than twice the average wage in the country. The analysis of online vacancies in Figure 5.17 indicates that the ability to provide advanced patient care is extremely relevant to the job, along with proficiency in several different medical knowledge areas such as paediatrics, gynaecology, oncology, and emergency and intensive care. Nurse practitioners blend these competencies with knowledge of therapeutic procedures such as electroconvulsive therapy, treatment of abdominal pain and its surgery, laceration repair, ear-nose-throat surgery and eye irrigations. As healthcare occupations will grow in importance in the next decade, so will the associated skills, potentially creating skill gaps that education and training systems will need to fill with adequate supply of qualified personnel.

Jobs like home and personal care aides already employ more than 3 million people in the United States and are expected to grow by an additional 34% in the next decade, eventually employing more than 4.5 million workers. Population ageing, and the associated need to support the elderly, are fundamental drivers of this labour-market dynamic. Unlike nurse practitioners, home and personal care aides are lower-skilled professionals (requiring on average a high school diploma or equivalent). However, their skills are hard to automate, given the various tasks they perform daily to assist people with disabilities, chronic illnesses or cognitive impairment in their basic living activities. Online vacancies reveal that these jobs also require familiarity with a heterogeneous set of medical concepts, such as geriatrics, mental health diseases and disorders, and acute renal failure treatment.

Interestingly, the skill bundles of home health aides and personal care aides feature innovative procedures, such as functional therapy, psychodynamic therapy (interpreting mental and emotional processes to help clients find patterns in their emotions, thoughts and beliefs, to gain insight into their current self) and even cognitive retraining. Other tasks and competencies associated with the profession involve more manual and physical abilities to support clients' living conditions, such as the ability to manipulate a stoma or perform glucometer tests or alcohol rubs.

Retraining pathways for the future: Evidence on skills and occupational mobility derived from online vacancies

The world of work is changing rapidly, and the impact of the COVID-19 pandemic will be felt for years to come as countries try to recover from this unprecedented shock. Many workers lost their jobs during the crisis, and many others saw their livelihoods decrease. Economic activity is set to restart as vaccines are made available to the general population, but uncertainty remains as to whether economies will be able to regain speed quickly and workers who have lost their jobs will be able to find new employment.

Returning to "business as usual" will not produce a sustained economic recovery (OECD, 2020[2]), as the world of work was already changing before the pandemic. Nevertheless, the current crisis can represent a turning point to "build back better", by tackling the emergency and the structural challenges posed by technological change, digitalisation and automation. Looking at the intersection between education, training and labour-market policy, this means that many workers will need to adapt to these turbulent times by returning to the labour market in different roles or even different occupations. These necessary transitions can only be achieved by supporting their retraining paths, so that they can develop vital new skills and competencies for today and the future.

This section mines information on the skills and knowledge areas detailed in 62 million vacancies advertised online in the United States for more than 700 different occupations between 2016 and 2018. The analysis unveils the most suitable retraining pathways that would allow individuals currently employed in occupations that are projected to decline to transition towards occupations that are projected to grow in the next decade. OECD (2019[20]) conducted a similar exercise (though at a much higher aggregation level) based on 2012 data collected in the Survey of Adult Skills, a product of the Programme for the International Assessment of Adult Competencies (PIAAC). This chapter provides selected examples of a set of occupations which are projected to decline sharply over the next decade or have been hard hit by the pandemic using the more granular and up to date information contained in online job postings.

In particular, as an example, this section analyses the retraining that would allow workers employed as executive assistants (occupations that are projected to decline by more than 20%) to move into occupations with a sufficient degree of skill similarity, such as administrative services and facilities managers (6% projected growth), or public relations specialists (7% projected growth).

Reflecting dynamics arising from the COVID-19 emergency, the chapter also considers the short-term retraining pathways needed to train educational, guidance and career counsellors (who experienced a 49% drop in vacancies during the crisis) to become community health workers (11% growth in online job vacancies over the same period). This is not to say that these career moves would be immediately desirable once the pandemic is brought under control but they are interesting to analyse as an example of how big-data could be used in the current context as guidance for policy makers to build short and effective retraining pathways. Of course, more and different career moves are possible and sometimes desirable, depending on individual characteristics or preferences. However, countries should consider using the real-time granular information contained in online vacancies to support the design – and especially updating – of retraining pathways and lifelong learning programmes, to support workers in their training and retraining decisions.

Retraining pathways for jobs projected to decline sharply: Evidence from online vacancies for executive secretaries and executive administrative assistants

The information contained in online vacancies makes it possible to identify the skill bundles, knowledge areas and tasks characterising different occupations. Since these characteristics may overlap, workers can make career moves by drawing on the skills and knowledge they use in their existing occupation and integrating new ones. For example, online vacancies for receptionists and information clerks share many of the same skill and knowledge requirements as file clerks, which differ vastly from those typically required of art directors or software engineers. A high degree of skill commonalities between two occupations facilitates career switching, as retraining will generally be shorter and less intense. Switching careers is also more or less difficult depending on whether the new occupation typically requires the same education level and on-the-job training to attain competence, and whether the career move implies a wage penalty or a wage increase.

The outer circle of Figure 5.18, illustrates the ten occupations whose skill bundles and knowledge areas relate most closely to those of executive secretaries and executive administrative assistants. The results are based on the information contained in online vacancies, which allows comparing the skill bundles of different occupations, ranking them from relatively dissimilar occupations to highly similar occupations in terms of skill requirements. Throughout the chart, lighter blue tones denote a closer skill similarity between the initial and destination occupation; a green colour indicates that the destination occupation is projected to grow by 2029 (see Table 5.1 and Table 5.2 above).

The inner circles of Figure 5.18, provide additional information on the typical education level (second circle from outside) and on-the-job training required to enter the job (third circle from outside). Lighter colours reflect more similar education and on-the-job training requirements between the initial and destination occupation. Finally, the innermost circle provides information as to whether a career move would imply (on average) a wage penalty, a wage increase or similar pay relative to the initial occupation (lighter colours indicate that the career move would lead to an occupation paying a higher or similar salary; darker colours lead to an occupation where the salary would be lower than in the initial occupation, hence more difficult to accept for the individual).

The results show that the "easiest" career move for executive secretaries and executive administrative assistants would be to work as first-line office supervisors and administrative support workers. In fact, the analysis of online vacancies reveals that both occupations share similar skill, knowledge and education requirements. Neither requires particular on-the-job training, and their wages are relatively similar. However, the employment rate of first-line supervisors of office and administrative support workers is projected to decline substantially (83%) in the next decade. Given the expected impact of technological and structural changes on jobs, forward-looking career moves should consider occupations that are in the "skill neighbourhood" of the initial occupation but are projected to grow over the next decade. Administrative service and facilities managers, and public relations specialists, fall within the skill neighbourhood of executive secretaries and executive administrative assistants (as depicted in online job postings information), but are projected to grow by 6% and 7% respectively in the next decade.

Administrative services and facilities managers typically plan, direct and co-ordinate an organisation's support services. They maintain facilities, perform administrative duties, and oversee the comfort, safety and efficiency of the built environment. Administrative services and facilities managers share various "administrative" skills with executive secretaries and executive administrative assistants, and typically engage in similar tasks. However, they also differ in a variety of aspects. Compared to executive secretaries and executive administrative assistants, administrative services and facilities managers have superior knowledge of facility management and maintenance and energy management, as well as planning, management and use of specific technologies (e.g. heating, ventilation and air conditioning [HVAC] technology) (Figure 5.19). Upskilling and training in the areas mentioned above would allow executive secretaries and executive administrative assistants to catch up on key knowledge areas required to perform the tasks of administrative services and facilities managers, while contributing many of the skills already developed in the initial occupation.

Public relations specialists typically create and maintain an employer's or client's public image by writing media releases, planning and directing public relations programmes, and raising funds for their organisations. Public relations specialists share various skills and knowledge areas with executive secretaries and executive administrative assistants, including the ability to plan and manage events. The two occupations differ most notably in that public relations specialists also engage in promotional campaigns, general marketing and marketing strategy. Many marketing and public relations campaigns increasingly happen on line, using social media tools such as SproutSocial (a social media management and optimisation platform that provides brands and agencies with a single hub for social media publishing, analytics and engagement across different social profiles). Executive secretaries and executive administrative assistants would generally need retraining in those areas to become public relations specialists.

Figure 5.18. Occupations in the “skill neighbourhood” of executive secretaries and executive administrative assistants

United States, 2016 to 2018

Note: Typical education needed for entry in executive secretary and executive administrative assistant occupations: high school diploma. Typical on-the-job training needed to attain competence in the occupation: none. The outer circle of the sunburst chart presents the ten occupations whose skill bundles are most similar to those of executive secretaries and executive administrative assistants. The degree of similarity is measured by applying ML algorithms (Doc2Vec) to detect closeness of skill bundles across all occupations in the information collected in 62 million vacancies in the United States between 2016 and 2018. The inner circles provide information about the typical education level associated with entering the job and the typical on-the-job training needed to attain competence in the occupation (as detailed in O*NET), as well as the median wage of each occupation relative to the initial occupation. Wage penalty is considered a career move that implies a 30% or more loss relative to the median value in 2019. Darker tones generally indicate more difficult career moves, i.e. those implying lower skill similarity, higher educational requirements, substantial on-the-job training or wage penalties compared to the initial occupation (executive secretaries and executive administrative assistants) and the destination occupation. Green colours identify occupations that are projected to grow in 2029.
Source: OECD calculations based on data from Burning Glass Technologies the BLS and ONET.

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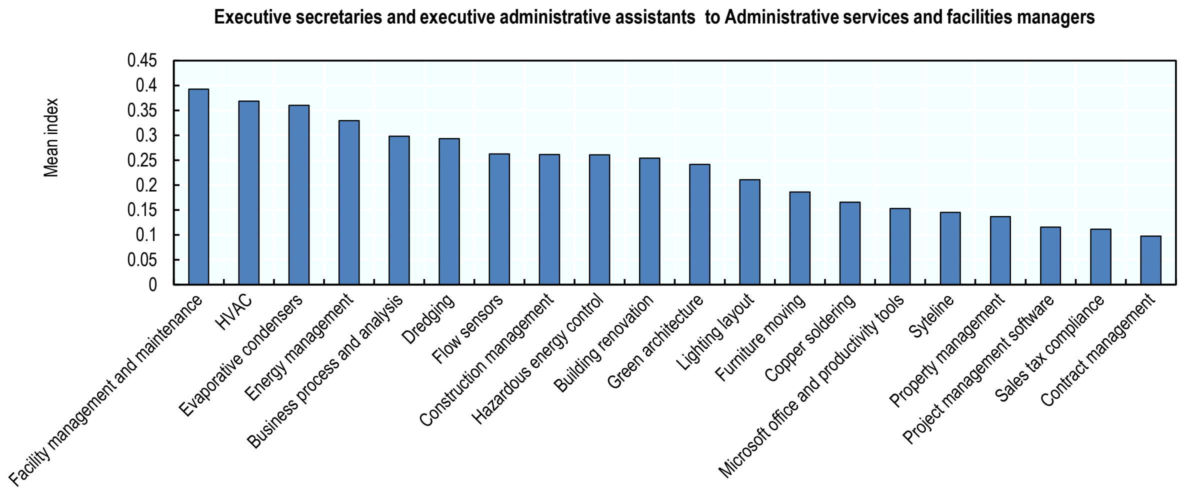
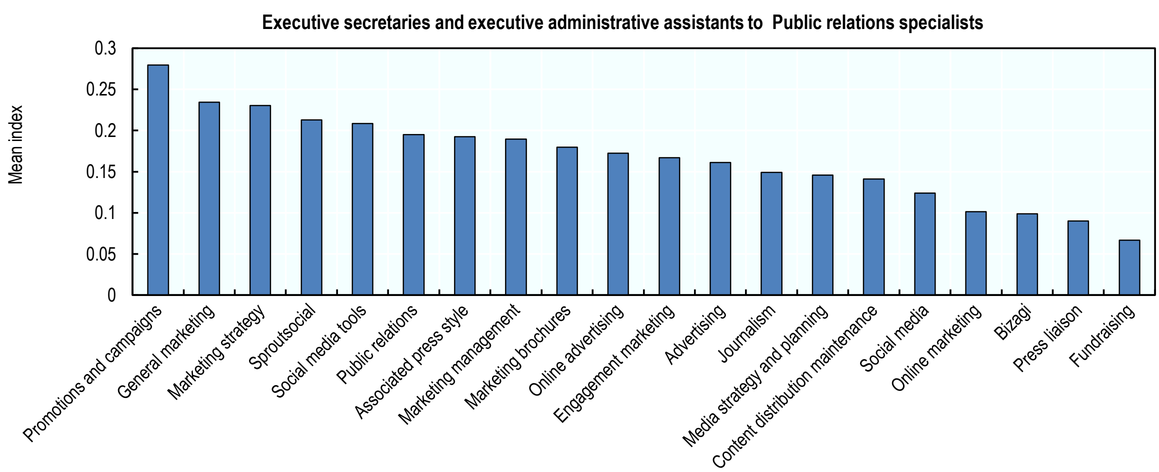
Figure 5.19. Top 20 skills executive secretaries and executive administrative assistants need to move to other occupations in their skill neighbourhood - average United States 2016 to 2018





Note: The charts present the 20 most important skills for the destination occupation, ranked by the distance between the skill profiles of the initial occupation and the destination occupation (y-axis). Positive values indicate that executive secretaries and executive administrative assistants would need to retrain/upskill in the skill under examination to move to the destination occupation in panel A or B. Conversely, negative values indicate a skill surplus. Values range from 1 (the largest possible distance between the initial and destination occupation in the skill under examination) to -1 (the largest possible negative distance between the initial and destination occupation in the skill under examination). More details on the methodology can be found in Annex 5.B.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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The COVID-19 crisis and the fast redeployment of workers through retraining pathways

The COVID-19 crisis has highlighted that the labour market can be slow in regaining its equilibrium, especially when facing a crisis of unprecedented magnitude. Personnel shortages in one part of the labour market may not be filled rapidly by surpluses of professionals in another part of the labour market, unless directed policy intervention is able to i) identify those workers who are best suited to fill those shortages; and ii) suggests quick and effective retraining pathways to fill gaps arising from the emergency.

The data contained in online vacancies can help policy makers identify workers who have experienced the sharpest declines in job openings during the crisis but who, given their skill set, would be suitable candidates to fill shortages through minor and short retraining for other occupations that have experienced surging demand. Designing skill-retraining pathways for an emergency situation is a much more complex undertaking than performing this exercise on occupations that are only slowly fading out because of technological progress. The sudden nature of the crisis makes it difficult to find suitable pairs of occupations with different labour-market prospects, but sufficiently close skill sets – not to mention other dimensions, such as educational and training requirements and wages.

The evidence in Table 5.3 identifies two such occupations in the current COVID-19 context. Data from online vacancies indicate that vacancies for educational, guidance and career counsellors have plummeted (-49%) during the pandemic, while demand for community health workers has increased by 11%. Yet these two occupations have relatively similar skill sets, which would allow redeploying from one to the other during the crisis with adequate retraining.

Table 5.3. Growing and declining occupations during the COVID-19 emergency

	Evolution of job postings during Covid-19 crisis (January-September 2020)	Median annual wage, USD, 2019	Typical education needed for entry	Work experience in a related occupation	Typical on-the-job training needed to attain competence in the occupation
Community health workers	11%	40 360	High school diploma or equivalent	None	Short-term on-the-job training
Educational, guidance and career counsellors and advisors	-49%	57 040	Master's degree	None	None

Note: Data on the evolution of online job postings during the COVID-19 crisis are calculated as the ratio between average job postings published for the occupation in January-February and the number of corresponding average job postings in September 2020.
Source: OECD calculations based on Burning Glass Technologies data and ONET (2021[31]), O*NET online, https://www.onetonline.org/.

StatLink https://stat.link/zfrtkx

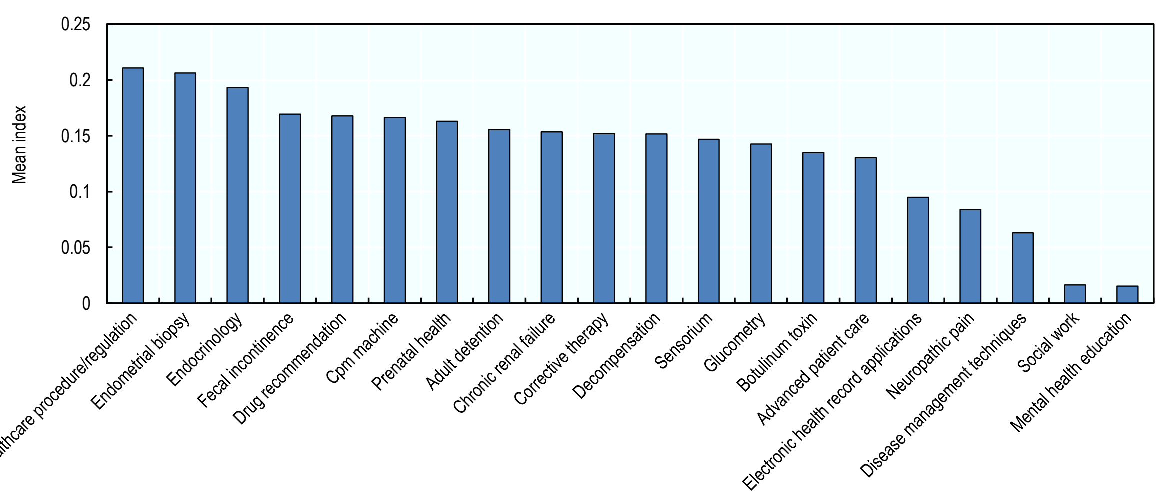
Community health workers provide and organise the delivery of basic health and medical care, and guidance to the community. Not only do they help patients navigate healthcare and social service systems and determine their eligibility for health insurance plans, they also provide informal counselling, health screenings and referrals. These tasks and skills are not far removed from those of educational, guidance and career counsellors, who also advise and assist individuals (students), and intervene when difficult situations arise in schools.

Information on skill requirements collected from online vacancies in the United States reveals that educational, guidance and career counsellors could be redeployed as community health workers through relatively minor retraining in healthcare procedures and regulations, as well as in different medical areas such as endometrial biopsy, endocrinology or drug recommendation (Figure 5.20).

Based on the granular information contained in online vacancies, a swift policy reaction could identify, in real time, which occupations are bearing the brunt of the crisis, designing short retraining pathways that will lead surplus workers to quickly fill new roles in high demand and emerging gaps in parts of the labour market affected by the emergency. However, caveats to this analysis do exist. First, the skills and knowledge areas identified in Figure 5.20 reflect the average tasks of community health workers in a pre-COVID situation, rather than those they may perform during the COVID-19 emergency. Extra care should be taken to adjust retraining paths to the current emergency situation. Second, the career moves depicted in this example should not be seen as being necessarily desirable in the longer run and once the pandemic is brought under control. In fact, educational, guidance and career counsellors, and community health workers, are both occupations that are projected to grow in the future, but that have been hit in a widely different way during the COVID-19 emergency. Going forward, however, policy makers should consider the use of such granular and timely information to closely monitor the evolution of their labour markets and adjust the supply of training and upskilling programmes accordingly.

Figure 5.20. Retraining pathways from educational, guidance and career counsellors to community health workers

United States data between 2017 and 2019



Note: The chart presents the 20 most relevant skills for the destination occupation, ranked by the distance between the skill profiles of the initial occupation and the destination occupation. Positive values indicate that retraining is needed in the skill under examination to move from the initial to the destination occupation. Conversely, negative values indicate a skill surplus. Values range from 1 (largest positive distance between the initial and destination occupation in the skill under examination) to -1 (largest negative distance between the initial and destination occupation in the skill under examination). More details about the methodology can be found in Annex 5.B.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

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Conclusions

This chapter provides a glimpse into the future of skill and labour-market demands. Looking forward to the recovery from the COVID-19 crisis, many firms have already announced plans to increase productivity by investing in automation. Such investments can accelerate the disruptive effects of technology diffusion, posing important challenges to vulnerable workers, particularly individuals with low skills and poor digital skills who would need to upskill to benefit from digitalisation and technological change.

In the aftermath of the pandemic, many workers who will be able to return to their previous jobs when economic activity picks up will still experience significant evolutions in skill demands and tasks. Other – less lucky – workers may not be able to re-enter the labour market in their previous roles, and will need to retrain and upskill to find a new job with new skill requirements. Here again, targeted and responsive lifelong learning is crucial for individuals to navigate such an uncertain and challenging landscape.

Against this backdrop, countries face substantial challenges in adjusting their education and training systems to the future of work. The projections used in this chapter show that declining occupations span different sectors, and that some of the skills used by workers today will become redundant in the future as tasks are automated.

In line with evidence provided throughout the *OECD Skills Outlook 2021*, the analysis in this chapter reinforces the message that lifelong learning will become even more vital given the expected acceleration in technology uptake. Governments face great challenges in keeping their policies relevant and targeted at ever-changing landscapes and demands. To aid economic recovery in the short, medium and long term, countries must minimise skills shortages, and ensure that upskilling and reskilling efforts are targeted and timely. They must identify not only the skills needed today, but also emerging trends and those industries and sectors that will most need those skills tomorrow. This information is key to facilitate career moves and align retraining efforts with labour-market needs, supporting individuals throughout their lifelong learning journey. When merged with traditional labour-market statistics, the information contained in online vacancies can provide policy makers with timely and targeted insight on short- and long-term challenges to support crucial policy-making decisions.

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Annex 5.A. A note on using online job postings to analyse labour-market and skill demands

Millions of individuals around the globe use new technologies every day to search for a new job, stay in contact with their professional networks, or gain insights into wages and employment opportunities in their (or other) occupations. Web platforms such as LinkedIn, Monster, Indeed, ZipRecruiter or CareerBuilder aggregate the information of millions of users and firms that rely on this marketplace. Virtually all these platforms provide their users with an “electronic labour market”, where millions of new jobs in all kinds of sectors are fields are advertised every day. Job postings (or advertisements) published on line contain textual information about the qualities employers look for in candidates, much as newspapers did in the past. The information contained in online vacancies ranges from the skills and tasks to be performed, to the advertised salary, job location, contract duration and many other aspects related to the working environment.

New advancements in automated web-scraping technologies (i.e. the automated retrieval and storage of textual information from the internet) make it possible to collect a wealth of information from online job postings to analyse trends in labour-market dynamics and skill demands with unprecedented granularity and timeliness.

The advantages of using the information contained in online job postings over traditional labour-market statistics, such as employer or labour-force surveys, lie in its richness, timeliness and granularity. First, unlike other data sources (e.g. O*NET[10] or ESCO[11]) based on the collection of survey information or expert opinions, the analysis of online vacancies allows tracking changes in skill demands over time and up until very recently. This feature of the data provides useful insights on the fast-changing labour market in the context of the COVID-19 crisis and also on evolving demand, making it possible to detect emerging trends, and predict better changes in the short and medium run.

Second, compared with existing skill databases, the detail and volume of the information contained in online vacancies significantly improves the granularity of the analysis, by enabling a close examination of specific skills that are generally grouped together in traditional data sources. This allows moving beyond the analysis of generic concepts, such as “knowledge of medicine” (assessed in other widely cited databases, such as O*NET), to more specific concepts, such as knowledge of endocrinology or anaesthesiology. This has important implications for the ability to build more granular projections of skill demands, retraining pathways and policy interventions to spur their development.

Finally, in addition to highly detailed skill-related data, online job databases contain a large range of additional metadata, including the qualifications and experience required to access a specific job, its geographical location (up to the county level), the name of the firm or employer advertising the job, the type of contract (permanent or temporary), and the type of work arrangements (i.e. whether the employee will work remotely). Many job advertisements also contain information on the salary offered.

This chapter uses information provided by Burning Glass Technologies covering 27 European countries, as well as Australia, Canada, the United Kingdom, the United States and New Zealand. The data are presented by a unique “job identifier” after a deduplication of job postings appearing in different web and career portals, ensuring that the same job is not counted more than once even if it appears in different web portals. Job postings are then mapped to different taxonomies, at the 6th digit disaggregation level of national and international classifications of occupations, which allows mapping to other employment and labour-market statistics. Burning Glass Technologies also puts considerable effort into harmonising the keywords found in the job postings. For example, words that have several accepted spellings are considered interchangeably and codified homogeneously for further analysis. Thus, the keywords “teamwork” and “collaboration” are combined into “teamwork/collaboration”.

However, not all keywords collected from job advertisements are, strictly speaking, “skills”. Many represent “knowledge areas” (e.g. endocrinology or mathematical modelling), others identify knowledge of specific “technologies and tools” (e.g. Python or Microsoft Excel), and others yet relate to “abilities” required to perform an occupation (e.g. physical or cognitive abilities). While these distinctions are meaningful, this chapter pools these categories together in the analysis and distinguishes between the different concepts when appropriate (Box 5.A.1). For the sake of simplicity, the remainder of the chapter will use the term “skills” when referring to these different dimensions globally, while the terms “knowledge”, “abilities”, “technologies” and “tools” will be used to distinguish clearly between the different concepts.

Box 5.A.1. Knowledge, skills, abilities, technologies and tools: What is what?

“Knowledge” keywords usually refer to an organised body of information of a factual or procedural nature which, if applied, makes adequate performance on the job possible. Examples are keywords such as endocrinology which when used in a job posting, denotes the required knowledge of all aspects related to the medical discipline and to the associated body of information.

“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 and skill in editing for transposed numbers.

“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. the 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 reference the ability to use that statistical software package in a work-setting.

Going ahead, more work is planned to clarify the distinctions among these dimensions in keywords collected from online vacancies in order to further enrich the analysis.

Source: Adapted from OECD (2017[32]), “*Getting Skills Right: Skills for Jobs Indicators*, https://dx.doi.org/10.1787/9789264277878-en.

The wealth and granularity of skill and labour-market information contained in online vacancies is unprecedented, but caveats and limitations to the use of these data also exist. For instance, Burning Glass data only cover jobs posted on line and may therefore not be representative of overall vacancies advertised offline.[12] In addition, online vacancies can be somewhat skewed towards certain areas of the economy. (Hershbein and Kahn, 2018[33]) document that healthcare and social assistance, finance and insurance, and education are overrepresented in Burning Glass data for the United States, while accommodation and food services, public administration/government and construction are underrepresented. However, most differences are small in magnitude. A recent OECD working paper assessed the statistical properties and distributional characteristics of online job posting data from Burning Glass, and how these changed over time (Cammeerat and Squicciarini, 2020[34]). This work suggests that most countries display adequate representativeness overall, when considering only those years for which no breaks in time series are observed. However, the study shows that occupational categories such as managers, professionals, and technicians and associated professionals are relatively more represented in Burning Glass data compared to other occupational categories. Caution should therefore be exercised when interpreting the results and comparing occupational categories or performing sectoral analyses.[13]

The potential bias is more pronounced for low-skilled jobs, and less of a concern for high-skilled occupations and sectors. In this regard, Carnevale, Jayasundera and Repnikov (2014[35]) estimate that around 80-90% of postings requiring at least a bachelor's degree are found on line, compared to 40-60% of job postings requiring a high school degree. That being said, Hershbein and Kahn (2018[33]), Forsythe et al (2020[36]) and Dalton, Kahn and Mueller (2020[8]) have linked Burning Glass data in the United States to the U.S. Job Openings and Labor Turnover Survey at the establishment level, finding a high degree of consistency between the two data sets.[14] Knutsson, Tsvetkova and Lembck (forthcoming[37]) also show that the regional distribution of Burning Glass data for Australia, Canada and the United States is generally well aligned with official data for the most recent years.

Annex 5.B. A note on the machine learning approach to the analysis of skill information contained in online job postings

Previous literature that used online vacancies to analyse labour market dynamics has, in most cases, counted the frequency with which skill keywords appear in job postings and used it to make inference about skill demands in the labour market. 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, derives a word's meaning from the context this occurs in (the distributional hypothesis). This approach is used in this chapter to both interpret the semantics of the keywords in the database as well as to come up with a strategy to categorise them into larger groups.

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. In essence, these *n*-dimensional vectors are lists of real valued numbers that may be plotted as coordinates in a high-dimensional space. This semantic representation is thus encoded and distributed over all the *n* dimensions of the vector, where each dimension stands for a certain context item and its coordinates refer to the count of this context (Erk, 2012[17]). Since this semantic representation is entirely built from real valued numbers, one can use similarity measures to reflect the similarity between different vectors representing different words (Boleda, 2020[38]).

Intuitively these arithmetic operations are retaining the semantic meaning of words and the results of such mathematical operations are, therefore, expected to return semantically and logically meaningful results. For instance, once word vectors have been estimated, one could perform basic arithmetic, such as: *vec("Queen") + vec("Male") = vec("King").*

From a mathematical point of view, this means that if two words share a similar meaning (for example Queen, King and Royalty) 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. In the context of online job postings used in this chapter, this can be used to extract the semantic meaning of each "skill keyword" contained and analyse them by drawing the relationships between, in our case, skill keywords.

In addition to word-vectors (representing skills), the vector representation of all occupations is also derived, using the concatenation of the skill vectors to form 'occupation vectors'. To facilitate this, the paragraph vector distributed bag of words (PV-DBOW) is used to determine the semantic meaning of both skills and occupations. Individual skill vectors were trained with the Skip-Gram variant of the Word2Vec package. The occupation vectors, empirically obtained using PV-DBOW, intuitively, represent the semantics of each occupation in a vector-form as they are constructed from the meaning of the skills that form the occupation, representing the skill requirements of a certain occupation.

Having calculated the vector representation in the *n*-dimensional space of both the skill and occupation keywords allows also to calculate the similarity of any given skill with every occupation vector calculated. This allows to assess, for instance, whether the vector for the keyword "Administration skills" is closer to the vector representation of the occupation "Economist" or to that of a "Painter". Note that 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. 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.

The similarity scores between each skill keywords and the occupation-vectors are calculated for all combinations of occupations and skills and the resulting values populate the Semantic Skill Bundle Matrix (SSBM henceforth).

Annex Box 5.B.1. Interpreting the semantics contained in online vacancies

The core objective of a language model is to understand the complex relationships between words (the semantic context) in order to predict the most adequate word (the output) in multifaceted situations such as translation, question answering and sentiment analysis.

When applied to the context of language and semantic analysis, *language models* aim to learn from the data the probability distribution related to a sequence of words so as to be able to either predict the words that should be following the one under exam or to assign probabilities to the likelihood of certain sentences to happen given the contextual information.

Word embeddings function by creating a mapping between words and their meaning (i.e. semantics) in so-called word vectors. These word vectors are, in practice, the mathematical representation of the semantic meaning of the words in a *n*-dimensional vector space where words with similar meanings occupy close spatial and mathematical positions in the vector space. Based on their meaning, for instance, the word ‘Queen’ and ‘King’ are likely to have similar word vectors and to be close in the mathematical vector space as they are also semantically related even if the letters of the alphabet that they are comprised of are totally different.

From an empirical point of view, estimating word vectors requires “fitting the data” or the “corpus” (i.e. the collection of all words to be analysed, in this case, the text of millions job postings) by solving an optimization problem. In particular, the ‘semantic analysis’ relies on the identification of the key text elements in the corpus (i.e. the set of all sentences) and the assignment of those elements to their logical and grammatical role in the semantic context.

To illustrate the type of information contained in the SSBM, an example is given in Annex Figure 5.B.1 for the occupations “Web-Designer” and “Marketing Manager”. Results in Annex Figure 5.B.1 show that the word vectors “Web Design”, “Bootstrap” and “Graphic and Visual Design” are semantically (spatially) close to the occupation “Web Designer” and, hence, are interpreted in what follows as the “relevant” skills to that occupation. Similarly, “Online Marketing”, “Marketing Management” and “General Marketing” are the relevant skills for “Marketing Managers”.

Annex Table 5.B.1. Example of skill bundle (selected top and bottom skills)

United Kingdom, 2018

Web Designer		Marketing Manager	
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
…		….	

Web Designer		Marketing Manager	
Electrical Engineering Industry	-0.06	Civil Aviation Authority	-0.04
Occupational Hygiene	-0.06	Fuel Meters	-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

Source: OECD calculations based on Burning Glass Technologies data, May 2021.

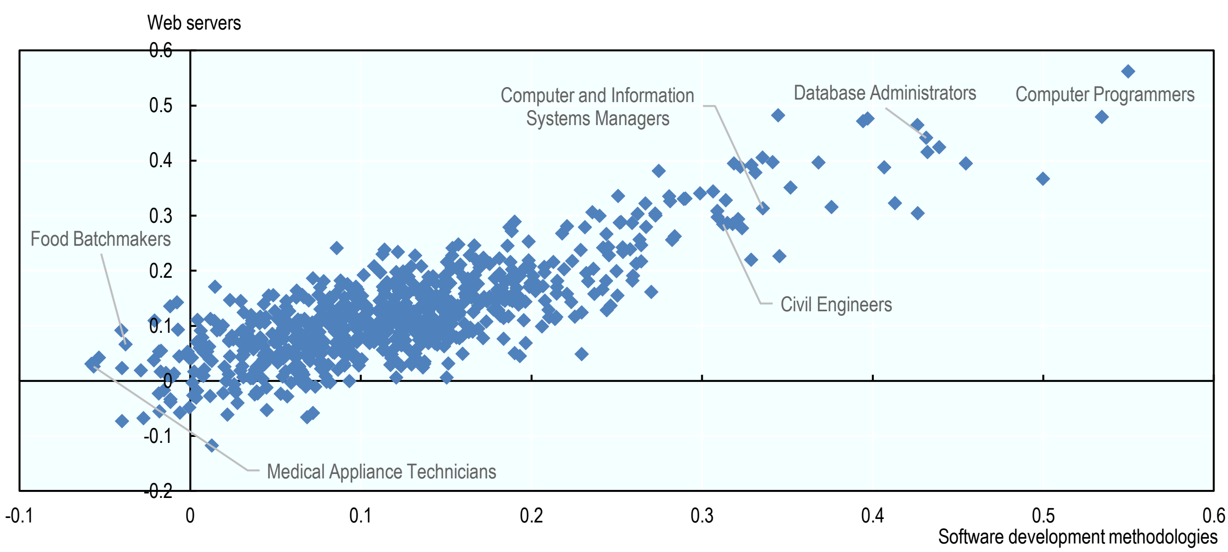
StatLink https://stat.link/v78i5y

In addition to creating a series of ranked values of the relevance of each skill for any given occupation, the structure of the SSBM allows to calculate the correlation between skills in BGT across the occupations. In practice, it is possible to know the extent of the correlation between each skill, unveiling the relationship between skills in the full body of online vacancies.

To exemplify this, Annex Figure 5.B.1 shows how the knowledge of 'Software development methodology' is associated to that of 'Web servers' across occupations, meaning that occupations where the former keyword is highly relevant are those where the latter is also relevant.

Annex Figure 5.B.1. Correlation between the knowledge of "Software development methodology" and that of "Web Servers" across occupations

United Kingdom, 2018



Note: Dots represent occupations, 703 in total in the United Kingdom, 2018. Correlation coefficient 0.82. The values on the axes come from the skill bundles matrix (e.g. the semantic distance of each of the two skills from the occupations analysed).
Source: OECD calculations based on Burning Glass Technology data, May 2021.

StatLink https://stat.link/92pqet

Annex Box 5.B.2. Applications of the Semantic Skill Bundle Matrix

Several applications are possible by exploiting the correlation matrix extracted from the skill bundles. First, one can explore what skills are more likely to appear together (on average across all occupations in the labour market). This could be useful to suggest an individual areas where she/he could potentially need to develop further (new) skills (if not already mastered) as the suggested skills are close matches to her/his own and are likely to be demanded in jobs of potential interest for the individual. For instance, results show that, on average, occupations requiring high levels of both “cloud solutions” and “database administration” skills are also highly correlated to “data warehousing” skills. A job-seeker with the first two skills, therefore, may want to consider developing the third, as this is likely to be in high demand in occupations related to her/his area of expertise.

Second, correlation analysis can also help to infer the relationship between key skills such as “artificial intelligence” and other complementary skills to it. Results show, for instance, that jobs requiring high levels of “artificial intelligence” skills are also very likely to require “machine learning” and “data science” as well as “big data” and others.

Annex Table 5.B.2. Correlation between Artificial Intelligence and other skills in the database

United Kingdom, 2018

Skills	Correlation With Artificial Intelligence
Machine Learning	0.86
Data Science	0.80
Big Data	0.78
Scripting Languages	0.77
Tensorflow	0.74
Internet Of Things (Iot)	0.73
Caffe Deep Learning Framework	0.73
Software Development Principles	0.72

Source: OECD calculations based on Burning Glass Technologies data, May 2021.

StatLink https://stat.link/0j5mo7

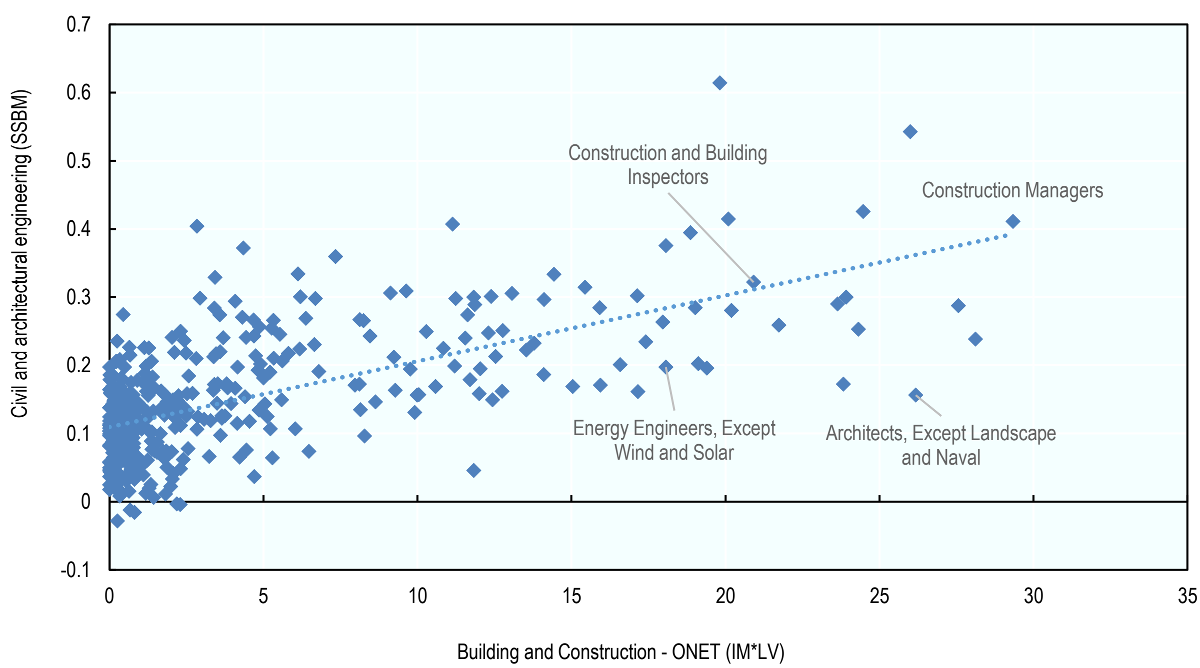
The values in the skills bundle matrix are built as a representation of the semantic similarity/dissimilarity of any given skill keyword relative to each occupation’s vector representation. From an intuitive point of view, the closer (semantically, in meaning, that is also in the *n*-dimensional vector space) a skill keyword is to an occupation and the more this skill plays an important role for that occupation (i.e. it is ‘relevant’ to it). In principle, the semantic similarity of a skill to an occupation can, therefore, be used to proxy for the importance of that skill in the specific skill bundle of the occupation under consideration. There are, however, no straightforward ways of empirically testing this hypothesis. One possibility is to use expert judgement and assessments about the importance of skill across occupations and compare that to the values of the skill bundle matrix.

ONET is a precious source of information in these regards as it provides a “concise index” of experts’ assessment of the importance and level of a wide range of skills across occupations. In ONET, experts and job incumbents are asked to rank the importance (and level) of a wide range of skills for each occupation (up to 6 digits) in the U.S. labour market.

By correlating the values of the skill bundle matrix with those in ONET across occupations, one is ideally able to establish whether the skill bundle's values built using the semantics analysis are a good approximation of the "importance and level" ranking given by ONET experts to each skill across occupations. One challenge is, however, that BGT's skill keywords differ from ONET's categories. As BGT keywords are much more numerous, they are also more granular and specific than the categories in ONET. As an example, while in BGT it is possible to find the keyword "Anaesthesiology", in ONET such skill would likely be categorised into a much more general label such as "Medicine and Dentistry".

Running a full correlation analysis between any given BGT skill and all ONET categories' values across occupations allows identifying the relationships between ONET categories and BGT keywords. Results in Annex Figure 5.B.2, show the correlation (coeff: 0.66) between the SSBM's values for Civil and Architectural Engineering (BGT) with Building and Construction knowledge (ONET). This correlation is positive and significant, confirming that ONET and SSBM's values are well aligned as expected/desired.

Annex Figure 5.B.2. Correlation between Civil and architectural engineering semantic skill bundle's (SSBM) values and Building and Construction knowledge across occupations in ONET (importance*level)



Note: The correlation coefficient between ONET values (computed as the product of the importance and level scores, IM*LV) and SSBM values is 0.65. Dots are ONET and SSBM values for occupations (6-digit US SOC).
Source: OECD calculations based on Burning Glass Technology data and ONET (2021[31]), O*NET online, https://www.onetonline.org/.

StatLink https://stat.link/kh1fj0

The results above confirm that the ranking of semantic 'relevance' of skills across occupations in the SSBM resembles the ranking of the importance and level in ONET (as provided by labour market experts and job incumbents) for skills/knowledge areas that are logically related to each other across the two data sources (i.e. in the cases above Anaesthesiology vs Medicine and Dentistry or Civil engineering vs Building and Construction in BGT and ONET respectively). In turn, this suggests that the values contained in the SSBM and their ranking across occupations can be used to proxy for the relevance of BGT skills across occupations as they produce strikingly similar results when compared to ONET values over the same occupations and in related skills, knowledge and abilities.

Annex 5.C. A note on the empirical assessment of the impact of transversal skills on wages and job openings

The analysis presented in the chapter estimates the association between wages, employment outcomes and transversal skills through a standard regression model run on a large panel of approximately 2 million online vacancies collected in the United Kingdom in between 2017 and 2019. The empirical model tests the following general specification in two variants (wage and employment):

$$\boldsymbol{lnY = \alpha + \beta_1 AvEducation + \beta_2 SkillComplex + \beta_3 Trans\_Skill + Geography + Sector + Time}$$

In the wage regression, InY is the log of yearly wages offered in each individual job posting. In the employment regression, InY represents instead the log of job openings in the specific occupation at the 6-digit level of the ISCO. Both specifications use the same set of regressors to estimate the returns on wages and employment. However, the employment regression aggregates all variables at the occupation level (6-digit) as the dependent variable in this latter specification is the frequency of job openings by occupation and geography.

AvEducation is the qualification title mentioned by employers in their advertisements. As job postings do not explicitly mention the number of years of education required, but instead only the desired qualification level (e.g. master's degree, doctorate or upper-secondary education), the title has been converted into average years of education using the standard International Standard Classification of Education.

SkillComplex measures the total number of skills mentioned in each job advertisement and is an indicator of the average skill complexity of the job opening under consideration. Jobs mentioning a larger number of skills are assumed to be more complex, requiring multifaceted combinations of skills.

Trans_Skills is a continuous variable that captures the relevance of each transversal skill under consideration for any given occupation. This measure is calculated by creating word embeddings of the textual information contained in online vacancies (see Annex 5.B), which allow representing the semantic meaning of keywords in mathematical vector form. Both skill and occupation vectors have been estimated through NLP and the use of word2vec and doc2vec ML algorithms. The semantic distance (i.e. cosine similarity) between skill and occupation vectors is used to approximate the relevance of the skill to the occupation. For instance, this ML approach makes it possible to disentangle whether leadership skills are closer and more relevant to managers than to plumbers. The empirical specification is run on a full set of sector and geography dummies (county level) as well as time fixed effects, and is repeated separately for each transversal skill in Figure 5.8.

In addition to the results presented in the main text above which look at the returns of each specific transversal skill, further analysis in Annex Table 5.C.1 investigates whether jobs that require a larger number of transversal skills receive higher or lower wage or employment returns. Results in Annex Table 5.C.1 show that, on average, job postings mentioning a large number of transversal skills are associated with negative wage returns (i.e. with wages that are below the average of the sample). The result is not unexpected. Jobs requiring a relatively large number of transversal skills are not, by definition, technical and specialised jobs and this is likely to lead to lower than average wage returns in the broad labour market. To put it in other words, results suggest that a certain degree of specialisation and of technical skills drives positive wage premium. That being said, results in Annex Table 5.C.1 also show that occupations requiring a relatively large number of transversal skills enjoy positive employment returns (i.e. more job openings than average). The results suggest that workers who master many different transversal skills can easily adapt to different job roles and perform tasks in a variety of occupations. To put it in other words, individuals mastering a large set of transversal skills are likely to be good candidates for a wider set of jobs, increasing significantly one's overall chances of being employed. Taking both wage and employment results together, the analysis in Annex Table 5.C.1 suggests the existence of a trade-off between what transversal skills can deliver in terms of an increased employability and the wage returns associated with them.

Annex Table 5.C.1. Average association between transversal skills intensity, wages and job openings

United Kingdom, 2017-2019

	Log (wage)	Log(openings)
Years of education	0.09***	-0.01***
Skill complexity	0.02***	-0.01
Transversal skills intensity	-0.02***	0.03***
Constant	8.94***	3.33***
Multiple R-squared	0.29	0.24
Adjusted R-squared	0.29	0.23
Observations	2289267	184943

Note: Results present coefficients of OLS regressions run on the number of years of education, skill complexity (i.e. the number of skills mentioned in each job posting) as well as on transversal skill intensity (i.e. the number of transversal skills mentioned in each job posting). Time and geography dummies are also added to each regression to control for unobserved heterogeneity. *** indicate that coefficients are statistically significant at 1% confidence levels.
Source: OECD calculations based on Burning Glass Technologies data, May 2021.

StatLink https://stat.link/5be7pm

Notes

[1] Initiatives ranged from stronger efforts to detect cases early and trace contacts with other people to ordering severe physical distancing measures, including full national lockdowns and economic shutdowns, except for "essential activities". Common measures included school closings, travel restrictions, bans on public gatherings, emergency investments in healthcare facilities, new forms of social welfare provision, contact tracing, and other interventions to contain the spread of the virus, reinforce health systems and manage the economic consequences of these actions (Hale et al., 2020[4]).

[2] The results presented here concern selected countries. The results for the full set of countries will be made available in online country notes.

[3] The stringency index is taken from the Oxford COVID-19 Government Response Tracker (OxCGRT), a systematic tool to track government responses to COVID-19 over time across countries and subnational jurisdictions. The project tracks governments' policies and interventions across a standardised series of indicators, and creates a suite of composites indices to measure the extent of these responses. The stringency index in particular contains information on containment and closure policies, such as school closures and movement restrictions. It records the number and strictness of government policies, and should not be interpreted as "scoring" the appropriateness or effectiveness of a country's response. For more information, see (University of Oxford, 2021[41]).

[4] Caveats apply to the interpretation of these disaggregated results. It should be noted that although the results are based on large samples of observations, job postings that explicitly state the minimum educational requirements make up a smaller share of the total vacancies: 32.3% of the full sample for the Australian sample, 38% for Canada, 25.6% for the United Kingdom and 60.5% for the United States. It should also be noted that low-skilled occupations are not widely advertised on line and may therefore be underreported in this analysis.

[5] This section analyses online vacancies published in the United Kingdom between 2017 and 2019. It uses the results for the United Kingdom as an example, since the transversal skills identified in other countries are qualitatively similar.

[6] Among the IT skills related to project management there are C shell-csh (a programming language that resembles C and that let users recall previous commands they have entered and either repeat them or edit these commands) and IPX/SPX (a network layer protocol).

[7] This chapter uses projections for the United States to illustrate the expected effects of megatrends (e.g. automation, digitalisation and population ageing) on economies that are at the technological frontier. The trends analysed here are therefore likely to be qualitatively similar and predictable in other countries. Moreover, the projections used here are produced at a high occupational disaggregation level, which allows capturing the effects of megatrends on employment trends with the necessary granularity for this analysis.

[8] Knowledge of trading relates to operations that consist of buying and selling a financial instrument within the same day, or even multiple times during the same day

[9] Previous studies by Vona et al. (2018[44]) and Chen et al. (2020[40]) used O*NET data to identify core sets of green skills, finding that the importance of green skills for Derrick operators is close to the maximum indicator.

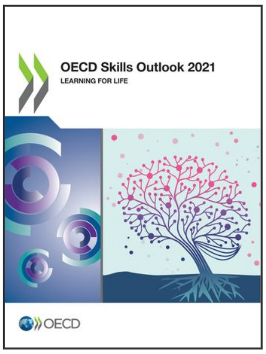
[10] (ONET, 2021[31]).

[11] (ESCO, 2021[42]).

[12] It should be noted that available jobs have been appearing increasingly on line, rather than in traditional sources (such as newspapers). For instance, an estimated 60-70% of all job postings in the United States could be found on line in 2014 (Carnevale, Jayasundera and Repnikov, 2014[35]).

[13] Depending on the aim of the study, reweighting the sample may be necessary. Moreover, the study shows concerns over representativeness of the data of Australia and New Zealand. Hershbein and Kahn (2020[39]) propose a reweighting-estimation-transformation approach to estimate the impacts of COVID-19 on job postings in Australia and overcome the problem related to the small sample size. Given the nature of the data and the scarcity of traditional statistics with similar frequencies, reweighting the data can be difficult. The results in this brief should therefore be interpreted carefully.

[14] Another point raised by Hershbein and Kahn (2018[33]) is that online vacancies "represent just one margin by which firms may adjust labour inputs through stated, but not necessarily realized, demand".



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