European Centre for the Development
of Vocational Training

EN

Understanding technological change and skill needs

Skills surveys and skills forecasting

Cedefop practical guide 1

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The **European Centre for the Development of Vocational Training** (Cedefop) is the European Union's reference centre for vocational education and training, skills and qualifications. We provide information, research, analyses and evidence on vocational education and training, skills and qualifications for policy-making in the EU Member States.

Cedefop was originally established in 1975 by Council Regulation (EEC) No 337/75. This decision was repealed in 2019 by Regulation (EU) 2019/128 establishing Cedefop as a Union Agency with a renewed mandate.

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Foreword

Cedefop has been at the forefront of developing robust skills anticipation methods and skills intelligence tools for the European Union for more than a decade. The European skills forecast and the European skills and jobs survey shed light on how the labour market, skill needs and jobs are developing and help signal potential skills bottlenecks. Cedefop's big data analysis of online job advertisements provides detailed and real-time skills intelligence, capturing which skills have currency in job markets. Cedefop has used skills foresight to develop stakeholder-backed policy roadmaps aimed at strengthening national skills anticipation and matching systems. Complementing quantitative skills analysis and intelligence, qualitative insight into skills policies and measures also contributes to evidence-based policy-making.

The continuing development of national skills intelligence systems and approaches has helped strengthen the feedback loops between the labour market and vocational education and training (VET) and skills policy. In the coming years, we need to be more ambitious. Our vision for Skills intelligence 2.0 is information that is more actionable: detailed and relevant, better contextualised, timelier, and better communicated. Making sense of trends and fostering capacity to act on them means combining sources and approaches – skill surveys, skills forecasting, skill foresight, big data analyses, and others – and exploring synergies. This gives policy-makers the means to separate noise from signal and supports employers and citizens in making decisions in line with the new realities in the world of work.

It is no surprise that skills intelligence is a key priority in the 2020 European skills agenda. Reliable and fit-for-purpose labour market and skills intelligence has enormous value in times of rapid change and transformation. In a context of fast-paced digital advancements, such as artificial intelligence and advanced robotics, and other megatrends such as population ageing and the green transition, VET and skills policies should become more proactive. To prepare new generations of learners and to support people in making and shaping career transitions, reliable skills intelligence is indispensable.

This publication is the first in a series of practical skills anticipation guides for policy-makers and analysts. The guides present a rich mosaic of conventional and emerging methods for identifying technological change and its impact on skills. Systematically presenting the merits and disadvantages of different methods, they show no single approach can provide all the answers. Apart from reliable data and sound methods, creativity, holistic thinking and using collective wisdom to shape the future are key building blocks of skills intelligence 2.0.

This first guide focuses on conventional methods of anticipating changing technologies and skill demands: skills surveys and skills forecasts. We trust the practical insights it provides will prove to be useful in your context.

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CHAPTER 1.

Technological change and skills

1.1. The fourth industrial revolution

Popular media and the vocational education and training (VET) and skills policy discourse highlight that technological change taking place in European firms is prevalent and fast-paced. The impression is that the world of work is at a crossroads of a fourth industrial revolution, being transformed by Industry 4.0, advanced robotics, artificial intelligence (AI), the internet of things (IoT) and other emerging technologies in a way that is more profound than previous waves of change, such as the one driven by the microprocessor revolution of the 1970s. This may or may not be true. But with forecasts suggesting that large shares of the current workforce are at risk of having their jobs substituted or transformed by automation (Frey and Osborne, 2013; Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018), the pressure is on those responsible for skills anticipation to come up with answers to several important questions.

Some of these are concerned with potential threats:

(a) which technologies are likely to emerge and become widely used over the short to medium term?
(b) what jobs will they impact?
(c) which skill sets are likely to become obsolete?

Others focus on opportunities:

(a) what new tasks and jobs will result from technological change?
(b) what skill sets do people need to acquire to fill those jobs?
(c) how does VET need to adapt?

1.2. Identifying technological change

Identifying and anticipating the pace of technological change in labour markets is challenging; an example is the early estimates of about half of all jobs in developed economies being at potential risk of substitution by machine learning algorithms (Frey and Osborne, 2013; 2017). These findings have been widely dismissed in several follow-up studies, which adopted alternative methodological approaches. Later estimates of the share of jobs disappearing due to automation based on a task or skills-based approach include using Cedefop's European skills and jobs survey and the OECD's (Organisation for Economic Cooperation and Development) survey of adult skills (programme for the international assessment of adult competences, PIAAC); these have been much lower than the early worryingly high predictions. Analysts have also looked at indirect indicators, such as total factor productivity, or direct measures of technological change. Such measures include the level of computer investment in an industry, the percentage of firms introducing particular technology (such as robotics or AI technologies) and the share of workers using new computer software or equipment (McGuinness et al., 2019). While all of these measures provide useful insights into how technological progress is affecting skill needs in labour markets, their measured effects can be piecemeal and the assumptions underlying them are sometimes challenged.

1.3. Understanding and measuring skills trends

To understand the extent to which technology is transforming the world of work, it is necessary to measure its magnitude and impact on skills demand. Labour market and skills intelligence (LMSI, often referred to as skills intelligence) provides such information and – provided that it is based on sound approaches and methods – can serve the needs of those responsible for reacting to changing skill needs. Such LMSI needs to provide information on the current situation and also reveal something about the future. Policy-makers are likely to have more opportunities to influence the future rather than the immediate skill supply. And if they are to make decisions that have some bearing on the behaviour of labour market actors, then they need to have sufficient level of detail.

Telling policy-makers and relevant stakeholders that the demand for people employed in professional occupations is likely to increase may not be of much value for them in making decisions about skills or qualifications requiring investment. They need to know job details and the specific skills attached to it. Similarly, if the concern is about the risk of automation wiping out jobs, there is a need to know which jobs. Simply saying that people employed in the broad plant and machine operator occupational group – as defined by the international standard classification of occupations (ISCO) – are more likely to engage in routine tasks, and hence face higher automation risk, is of limited value to a decision-maker. There is a need to know which specific jobs within that occupational category are at risk (Freeman et al., 2020).

It is often the case that the tasks and skills within a job need to be the focus of attention, especially the degree to which they can be rendered obsolete or new ones created (Deming and Noray, 2020). It is often not so much the job which is at risk, but rather particular tasks and skills required to carry out that job. By focusing on the latter, there may be a better chance to offset the risk that automation might pose to some jobs. This will be feasible by equipping affected individuals with the skills that the reconfiguration of work implies following the adoption of a given technology.

But what is meant by skill? It is a word or concept which is freely used without much certainty that it means the same thing to different people or labour-market actors. Before considering how data on current and future skill demand related to technological change can be collated, it is necessary to agree on common use of terms.

A skill is any capability that satisfies some practical requirement of a job but it is an elusive concept to define (Attewell, 1990). Economists' definitions of it have been largely driven by an interest in estimating the returns to human capital investments (Becker, 1962; Mincer, 1974). Skill is largely defined with reference to its capacity to deliver a financial return; a higher return suggests a higher skill level. By contrast, within psychology, the concept of skills typically refers to the qualities workers possess and the capabilities required for accomplishing certain work tasks, often referred to as competence. Sociologists have also been mostly concerned with the ability of individuals to respond to work complexity and the value of skills as part of social processes.

The skills required by jobs are diverse and multidimensional, and they can be specified in potentially infinite levels of detail. No survey or study can capture all skills involved in a particular job because any description of what a job entails can always be enriched with further detail. There is also a tension between detail and comparability across occupations: very detailed measures tend to be occupation-specific, while overly general measures risk being weakly informative. The key is to measure transversal skills and to devise measures pitched at a mid-level of generality that are relevant across a range of occupations. It should also include a reasonably concise checklist of more specific requirements, such as an inventory of digital skills, which are particularly relevant for research and policy. Most of the interest in skills and job-skill requirements typically focuses on a division of the concept at a most general level into cognitive, interpersonal, and manual skills. Interpersonal or 'soft' skills have proven to be weakly conceptualised, as they also often include more purely attitudinal and motivational aspects of work orientations (Moss and Tilly, 2001). By contrast, cognitive and manual skills tend to be more concisely measured and are usually associated with robust labour market outcomes for individuals.

In econometric equations, skill has been often defined with reference to occupation and/or qualifications which are, at best, proxy measures of the phenomenon. Because data on occupations and qualifications – measured at international level by ISCO and the international standard classification of education (ISCED) – are readily available, they are typically used as measures of skill in economic studies. This holds even though there is no guarantee that the skills acquired in obtaining a qualification are actually used by the individual in their job, giving rise to skill mismatches (McGuinness et al., 2018).

Given the difficulty in clearly defining the meaning of skill, analysts and labour economists have embraced the concept of job-skill requirements (Handel, 2012). Job-skill requirements, in short, refer to the specific tasks which comprise a job and the skills needed to undertake those tasks proficiently. With the emergence of surveys that have collected data on job-skill requirements, more detailed understanding has been obtained of the tasks which comprise a particular job and the skills which are needed to carry out those tasks successfully (Green, 2013). The job-skill requirements approach was pioneered in the UK's skills and employment surveys, which have been periodically carried out since 1986; it and is central to the OECD's survey of adult skills (PIAAC) and the skills, technology and management practices survey (STAMP) conducted in the USA (Handel, 2016; 2017). To give an idea of the type of information collected using the job-skill requirements approach, Table 1 summarises the skills information collected by the STAMP survey of workers.

The importance of the job-skill requirements approach is that it provides the basis for better understanding the relationship between skills and technology, including the risk of skills obsolescence and job loss resulting from technological change. There is a strong focus in the literature on identifying jobs or occupations that comprise a range of work activities that are more or less susceptible to being replaced by automation. The work of Autor and colleagues (2003) is groundbreaking in that it appears to have made the first use of the *US Dictionary of occupational titles* (DOT) to provide information about the nature of the tasks performed within occupations. The analysis suggested a hollowing out of the labour market, given that routine jobs – mainly those located in the middle of the occupational hierarchy (skilled trades and machine and assembly workers) – can be more easily substituted by machines, than jobs at the lower and higher ends of the jobs spectrum.

More recent analysis, such as that based on the Cedefop European skills and jobs survey (ESJS), suggests that automation can affect some tasks within a job, but not necessarily every task (Pouliakas, 2018). This means analysis must look in detail at intra-occupational task change resulting from technological change. The key point here is that, in understanding the nature of the relationship between skills and technological change, one needs to be precise in identifying skills affected by technological change, rather than solely focusing on whole jobs or occupations.

Table 1. **Skill measures used in the skills, technology and management practices survey**

Skill and task requirements • Cognitive skills (maths/numeracy, reading, writing, problem-solving) • Interpersonal skills (including teamworking) • Physical job demands/physical skills **Computer use (digital skills)** • Computers • Frequency of use • Use of 14 specific applications • Use of advanced programme features • Job-specific and new software • Training times • Complexity and computer skills required • Adequacy of respondents' computer skills • Computer experience of non-users in previous jobs	**Machinery and electronic equipment** • Set up maintenance and repair • Equipment and tool programming • Mechanical and electronics knowledge **Supervision, autonomy and authority** • Closeness of supervision, autonomy and repetitiveness • Supervisory responsibilities **General measures of skill** • Required education for job • Required experience • Employer-provided training • On-the-job training • Training in specific skills (literacy, math, customer service, sales, managerial skills, communication, quality control, technical skills)

Source: Handel, 2017.

1.4. Collating skills intelligence

Provided that an analyst has a good grasp of which skills to measure and how, what data collection approach offers insight into the impact of technological change on them? Something is required that delivers detail and, in an ideal world, insights into future skill needs. This is not straightforward and, to date, no single approach to skills anticipation has managed to reconcile fully the provision of both detail and a future-looking perspective. However, improvements are continuously being made and many skills forecast approaches are pushing the boundaries with respect to the amount of occupational detail that can be provided.

But there are problems, too. Where data are often provided on the current situation of a labour market, it is often the case that information is already dated because of the time lag between data collection and the publication of findings. This results from the rigour with which official statistics are collected, cleaned, and weighted before publication. The future is also becoming more volatile in some respects. The types of technology which are being introduced, and the speed at which this takes place, the way in which they transform work organisation and the types of skill needs this gives rise to, may be without historical precedence.

The sophisticated extrapolation of time series data into the future, typically applied by economists, may be misplaced if the past becomes a less reliable guide to the future. This perspective is sometimes criticised as an exaggeration because technological innovation tends to become mainstream at a slower pace than some commentators suggest (Bessen, 2016). It can be argued that conventional methodologies and tools at hand to examine the relationship between technological change and skill demand remain robust and reliable.

Table 2 summarises some of the main methods that can be used to gather information on skills needs. Four are particularly important:

(a) ask questions to key stakeholders (questionnaire surveys of employers' and employees' skill needs and experience of technological change);
(b) produce quantitative estimates of future skill demands, by extrapolating past trends and modelling expected developments;
(c) source 'big' data on new technologies and skills from a variety of online sources (for example job portals, CVs, social media, patents, scientific databases);
(d) use non-quantitative techniques, relying mostly on participatory stakeholder approaches to gauge in-depth information about the state of current and future skill demand and supply.

Table 2. **Tools for carrying out skills assessment and anticipation**

Type of activity	Data collected
Descriptive statistics/ stock taking	Estimates of overall demand and supply of skills and technology use, often based on collating data from various sources (for example, sector skill studies)
Quantitative forecasting	Forecasting or projecting future demand for skills typically using econometric modelling
Skills and jobs surveys (questionnaire surveys)	Assessments of demand for, and supply of, skills and technology use, usually with an assessment of the extent to which demand and supply are in balance
Graduate tracer studies	Using matched administrative datasets or surveys to track people through education and the labour market to see how the former influences the latter
Qualitative research	Use of non-quantitative techniques to gauge in-depth information about current and future skill demand/supply and technology trends, e.g. via company case studies, use of focus groups
Foresight	Critical thinking about the future of skills supply/demand and technology trends using participatory methodologies
Big data	Use of web sourcing combined with text mining and machine learning approaches to collect and classify data about skills, vacancies, technologies

Source: Cedefop classification.

1.5. Purpose of guides

This first Cedefop ‘how-to’ guide on understanding the impact of technological change on skill demand, focuses on conventional approaches to skills anticipation that typically employ quantitative methods, notably econometric forecasting and survey-based analyses (such as employer and employee surveys).

These are non-participatory approaches to skills anticipation in that they do not require stakeholders to be involved in deriving estimates of the impact of technological change on skills. There is no normative element as is present in participatory approaches, such as foresight, where the aim is sometimes to bring about a certain outcome, as covered in the third guide of this series ([1]). The approach in this guide is on collecting representative data to produce robust and reliable findings, using scientific statistical approaches.

This differentiates such methods from the increasing use of big data and AI-driven data analysis, which is a new method in the toolkit of analysts. While such big data approaches – covered in Cedefop's second guide ([2]) – are innovative, they cannot fully substitute for conventional statistical methods based on random probabilistic approaches. A guiding principle of all Cedefop guides, however, is that the best skills intelligence can be obtained by combining various types of analysis in a way that will reveal a holistic and robust view of emerging trends and their likely impact on skills demand in labour markets.

This guide is structured as follows. Chapter 2 focuses first on the development and implementation of employer or worker skill surveys, as a means to extract information of the use and impact of technologies at work. Chapter 3 then turns to the use of more elaborate skills forecasting quantitative models and ways of modelling technology trends in them. Chapter 4 concludes with a discussion on which LMSI is best to choose and the reasons for doing so.

([1]) Cedefop (2021a). *Understanding technological change and skill needs: technology and skills foresight. Cedefop practical guide 3.* Luxembourg: Publications Office. http://data.europa.eu/doi/10.2801/307925

([2]) Cedefop (2021b). *Understanding technological change and skill needs: big data and artificial intelligence methods. Cedefop practical guide 2.* Luxembourg: Publications Office. http://data.europa.eu/doi/10.2801/144881

Box 1. **Cedefop practical guides on understanding technological change and skills demand**

The purpose of Cedefop's short 'how-to' guides is to provide those with a responsibility for undertaking skills assessment and anticipation with the means to deal with the uncertainty of technological change and its impact on skill needs.

As the process of predicting the future becomes more complicated and less deterministic, the range of tools available to those involved in skills anticipation has become more varied and sophisticated. The Cedefop guides aim to showcase to policy-makers and interested analysts how various techniques or methodological tools can be readily applied, by carefully considering the associated pitfalls and rewards of doing so.

The guides provide targeted information on how interested analysts can adopt and implement conventional labour market and skills intelligence methods, such as skills surveys and skill forecasts; automated methods reliant on big data and artificial intelligence (AI) techniques; or technology foresight methods. All can be used to detect emerging skill needs related to technological change. Implicit in the guides is recognition that no one methodology is likely to provide all the answers and the challenge for analysts is to bring together outputs from different approaches to skills anticipation.

The guides build on the existing compendium of guides on skills anticipation produced by the ETF, Cedefop and the ILO ([3]), as well as several previous Cedefop reports on skills anticipation methods ([4]). But they are distinct from previously published methodological handbooks or guides, in that they are explicitly concerned with the process of identifying technological (digital) change, a key driver of changing skill needs.

Source: Cedefop.

([3]) https://www.cedefop.europa.eu/en/news-and-press/news/first-comprehensive-compendium-guides-skills-anticipation-methods

([4]) For instance, see ETF et al. (2013), Cedefop (2015) and Cedefop's project Anticipating and matching skills.

CHAPTER 2.

The art of asking questions: employer and employee skills surveys

Employer and employee skill surveys can be used to collect data on the introduction of technological change and how it has impacted on skills demand among a representative cross-section (or panel) of companies, workplaces or workers. It is often more useful and practical to conduct a survey of workplaces rather than multi-site companies, because respondents are typically better able to answer questions about their direct work environment, compared to questions about the bigger company that their workplace may be part of. While typically referred to as worker surveys, surveys among individuals can also be among economically active individuals in a wider sense.

2.1. Employer skills surveys

Employer surveys can provide relevant information on the following aspects of technological change and its implications for skill demand:

(a) prevalence of technological change (for example, the extent to which an establishment has introduced new machinery, equipment or technology over the recent past for reasons other than routine replacement) and plans to introduce technology in the future;
(b) vacancies and the extent to which they are hard to fill because applicants lack the skills, qualifications or experience required. Such information can typically be disaggregated by occupational group;
(c) internal skill gaps (for example the extent to which current staff is fully proficient at their jobs, again this can be disaggregated by occupational group);
(d) provision of workforce training.

Potentially this allows for analysis of the relationship between investments in various kinds of technological equipment and levels of skill shortage vacancies and internal skill gaps. If the data can be disaggregated by occupation, it is possible to gain insight into the extent to which technological change affects skill demand and whether that skill demand can be met by either the company's existing workforce or via external recruitment.

There are, however, some caveats: the capacity of the employer to report correctly the extent of technological change; and the tendency of some employers to overstate skill shortages because it may be in their interest to do so, if they want to see the supply of certain skills increased (Gambin et al., 2016).

Asking employers about the future usually produces mixed results. While some employers have a good overview of the current and future challenges they face, others are less prepared and are likely to consider the future only at the point at which it arrives. A Dutch sectoral study, where firms were surveyed on current and future employment developments, clearly illustrates this. In some cases, the average predicted future demand coincided with reality one quarter later but this was by no means the case in many other instances (Fouarge et al., 2012). In a heterogeneous population of employers, some will be using cutting-edge methods to predict future employment, while others will be doing next to little skills assessment, if any at all.

There is also a risk that planned technological change is under-reported. The German vacancy survey, a representative establishment survey with more than 10 000 responses, included, in its 2016 round, a series of questions on anticipated changes relating to digitalisation over the next five years. More than half of the respondents said that they did not expect digitalisation (internal digital networking, networking with customers/suppliers, or the use of learning systems) to increase over the next five years. If true, this is a remarkably low share of employers affected by technological change (Warning and Weber 2017; 2018). Perhaps some employers simply do not think that far ahead. While digitalisation trends can be identified to some degree, the timing and the speed of change are hard to measure. Repeated (similar) surveys among similar (or the same) firms, carried out in order to pinpoint the speed and convergence of new technologies, trends and skills required within organisations, can help overcome such problems.

Employer skill surveys are not particularly suitable for collecting information on how the content of jobs (occupations) in the workplace is changing, and the extent to which changes have emerged because of technological change of some kind. Company respondents (chief executive or personnel manager) find it difficult to answer questions about different categories of workers, especially if it is a large workplace. Cedefop's pilot employer survey on skill needs (Cedefop, 2013) made some headway in this regard, by collecting data on the importance of various transversal and occupation-specific skills in selected occupations and whether or not this importance has changed over time. In this way the survey was able to incorporate a skill requirement type approach. But widely implementing a detailed occupation-based employer survey can be costly. It may also be challenging to overcome serious methodological constraints, related to the sampling registers capturing the occupational distribution within companies or establishments across different countries (Cedefop, 2013).

The 2019 fourth European company survey (Eurofound and Cedefop, 2020) contains information on technology use (including use of computers and software, robots, use of data analytics), the extent to which employees' skills are matched to their job, and the pace at which the job content changes. Based on the questions asked, it is possible to gain insight, other things being equal, into the relationship between technology use and skill needs and mismatches in the workplace. However, such information is collected at an aggregate establishment level, giving rise to potential ecological fallacies that occur when inferences are made about individuals drawn from groups that they may belong to.

Table 3 provides a summary of the issues to consider when thinking about using an employer survey to explore the link between technological change and skills. It is effectively a checklist of what needs to be considered before commissioning such a survey.

Table 3. **Issues to consider before launching an employer skills survey**

Issues	Detail to be considered
Initial check	Do similar data already exist elsewhere?
Types of questions that can be asked about technologies	• Introduction of technological change over the recent past (e.g. last 12 months)? • Adoption of specific technologies (e.g. computers, robots, AI)?
Types of questions that can be asked about skills	• Occupational structure of the workforce (e.g. at ISCO one or two-digit level) • Typical qualification level required to get a job in each occupation • Vacancies and recruitment difficulties (disaggregated by occupation) and reasons for difficult-to-fill vacancies • Extent of internal skill gaps (disaggregated by occupation)

Issues	Detail to be considered
Survey requirements	• Sampling frame from which to derive a representative sample of the population of employers of interest • Need to assess whether a company survey or establishment-based one is required. Establishment-based surveys are easier because the respondents tend to find it easier to answer questions about the workplace at which they are based
Data collection steps	• Specifying hypotheses to be addressed • Specifying the variables and their relationships required to test the hypotheses • Drafting questions that will allow variables to be constructed (the questionnaire) • Crosschecking questions with other surveys (to allow for comparisons) • Design of sample (random probability, quota sampling, etc.) and sample size required for robust estimates to be derived • Type of survey (face-to-face, telephone, online, etc.) • Fieldwork • Weighting dataset to population estimates by employer and by employees employed in the workplaces sampled
Selected further literature	• ETF, Cedefop and ILO Developing and running an establishment skills survey Cedefop User guide to developing an employer survey on skill needs • Cedefop and Eurofound: European company survey

Source: Cedefop

2.2. Employee skills and jobs surveys

Employee surveys can be more successful in capturing information about technological change and changes in the skill content of a job (especially various transversal skills, such as numeracy, literacy, digital skills), because they target individual workers directly impacted by it. The example of the STAMP approach provided in Table 1, which has also been used in other recent international surveys, such as the OECD's survey of adult skills, the World Bank's Skills towards employment and productivity (STEP) survey and Cedefop's European skills and jobs survey, demonstrates how the concept of skill can be operationalised for data collection purposes.

There is the possibility that employees may exaggerate their skill or technology use levels, borne out of a reluctance to acknowledge that they are at a lower level required by their job or at a low level overall. Nevertheless, it can be beneficial to undertake an employee survey because of the possibilities it offers to collect information about:

(a) the employee's use (and level of use) of technologies at work and their experience of technological change in the workplace over a given time period;
(b) the employee's perception of how well their skills are matched to their current job;
(c) the employee's rating or assessment of their skill level, according to cognitive and other skill batteries or tests;
(d) the importance of various skills to an individual's job (for example how often they use those skills) and the level at which specific skills are held;
(e) how the skill or task content of their job has changed over time.

With respect to skills in particular, questions tend to be asked on:

(a) required skill level;
(b) whether the respondent possesses the requisite level of skill or exceeds it;
(c) the frequency of skills use;
(d) the importance of skills to the job;
(e) the level of complexity of skills in the job;
(f) how importance, frequency of use, and level of skill or complexity have changed over time.

2.2.1. Job-skill requirements approach

In the past, a lot of skills analysis relied upon using occupation and qualification as proxy measures of skill. These are imperfect measures. Broad occupation or education categories are coarse, roughly ordinal at best, and do not provide information on which skills are increasingly affected by technological change. Early employee skill surveys asked workers directly about their self-perceived level of skills, their importance for doing their job or how well-suited they are to fulfilling job requirements (see Cedefop's first European skills and jobs survey). The OECD's survey of adult skills (PIAAC) devised a more objective approach to assessing the skill level of individuals for three foundation skills:

(a) literacy;
(b) numeracy;
(c) problem-solving in technology-rich environments.

To overcome the drawbacks associated with previous self-reporting approaches, such as lack of objective anchors/yardsticks leading to personal interpretations by different (groups of) respondents, recent skills surveys have increasingly adopted the job-skill requirements methodology (Handel, 2017). This aids careful definition and operationalisation of the concept of skill needs, and has been a valuable development in the field. The job-skills requirements approach asks survey respondents about the specific tasks which comprise their jobs; these are usually mapped to specific skills, for instance cognitive, interpersonal, manual or digital skills, required to carry out the job successfully. Information on complexity of skills required in a job is typically obtained via incremental scale questions, which ask workers whether they undertake basic or more complex tasks in their job (Box 2).

Box 2. **Questions based on a job-skill requirements approach**

As part of your main job, do you regularly/did you do any of the following in the last (reference period):

- Read any texts that are at least one page or longer/five pages or longer, etc.?
  → Literacy skills
- Lift or carry heavy objects or loads?
  → Manual skills
- Use basic mathematics, for instance addition, subtraction, multiplication or division?
  → Numeracy skills
- Use any computing devices to send emails?
  → Digital skills
- Etc.

Source: Cedefop second European skills and jobs survey (ESJS) and STAMP (see Handel, 2017).

The job-skill requirements approach uses explicit scaling, asking questions about workers' regular activities carried out at work, translated into objective metrics (for example time or number of pages), rather than relying on abstract or vague questions on skills that are open to subjective interpretation and social desirability biases. Questions are general enough to encompass diverse work situations, but at the same time sufficiently concrete to have stable meanings across respondents. The job-skill requirements approach lends itself to surveys of individuals better than employers, simply because in an employer survey the respondent will inevitably be asked to report on a wide range of jobs, some of which the respondent might not necessarily be familiar with.

The objective, validated and standardised method of measuring job-skill demand administered consistently to representative samples of workers over time has aided understanding of the ways work is changing (Handel, 2003). The STAMP survey in the US (Handel, 2016), OECD's PIAAC survey and Cedefop's second European skills and jobs survey are notable examples of the job-skill requirements approach, which collects, in addition to information on the level of education required by the job and the duration of job-specific training, insights on the levels of cognitive, manual, interpersonal and ICT skills required in jobs.

Box 3. **The job-skill requirements module of Cedefop's second ESJS**

Building on the US STAMP survey, the second European skills and jobs survey collects, via a dedicated job-tasks module, information on the following job-skill requirements in EU workers' jobs:

Cognitive	**Manual**	**Interpersonal**	**Digital**
• Reading • Writing • Maths • Problem-solving • Creativity	• Lifting • Dexterity • Repetitiveness/ standardisation • Use of computerised machines	• Counselling • Selling • Serving • Presenting • Teaching/ training • Persuading/ negotiating • Caring • Teamworking	• Email/internet/ social media • Word processing • Spreadsheets • Data management • Occupation-specific software • Programming (AI)

It employs an incremental Guttman scaling approach that enables identification of higher or lower job-skill requirements in jobs. It also focuses on the discrete use of a specific task as part of an employee's main job in a given (one-month) reference period.

Source: Cedefop second European skills and jobs survey questionnaire.

The application of the job-skill requirements approach in a survey requires overcoming several challenges during its design stage. Decisions need to be made on how the survey will capture the regularity or periodicity whereby workers carry out some of their job tasks and if the focus should be on systemic or crucial job features, even if the latter are carried out occasionally. For example, it needs to be decided whether the focus should be on whether workers do a specific task regularly as part of their job, or frequently (a greater proportion of their working time) or if the task has been done at all within a given reference period? The dimension element is also important: how to strike a right balance between asking workers about a relatively broad or a detailed set of tasks?

It is important to be aware that respondents' answers may be affected by the inclusion or not of a reference period in the question. For some workers, tasks that are carried out at least weekly or monthly may appear to be important, while for others, tasks that require a higher level of skill complexity may be carried out rather infrequently and out of scope of the time span allowed for in the reference period. Answers to job-task questions are also likely to be affected by the response scales used. Response scales can be designed to question whether a job task is carried out at all (yes or no option), how frequently it is carried out (every day/at least once per week, etc.) or what share of a daily working time a task represents. The response scales may have to vary across different job task categories. Finally, the quality of responses to the job-task questions is linked to the interpretability of the formulation used in describing tasks and may be affected by the survey mode (face-to-face, computer-assisted telephone interviewing (CATI) or online) and environmental context (for example questions on carrying out specific ICT tasks may be affected by the recent coronavirus pandemic or other shocks).

2.2.2. **Capturing technological change**

As well as asking questions about skills, there is a need to think about how to capture information about technological change affecting workers' jobs and skill needs. Previous efforts to do so have tried to measure the type of technological change being introduced, such as plant, machinery and equipment, or the introduction of new software or some combination of changes. In the absence of individual microdata, technological change is typically proxied with reference to investment in computer equipment (for example Autor et al., 2003), or firm automation costs defined as costs of third-party automation services (Bessen et al., 2019) or computer-related occupational job task changes (for example Deming and Noray, 2020). Such analyses typically combine data from several data sources to analyse change at the level of the job/occupation rather than the individual.

In worker skill surveys, where the aim is to understand the impact of technological change, it is likely that its impact on jobs and skills will be shaped by a range of internal factors:

(a) the type of technology being introduced;
(b) the approach the company takes to introducing change (for example the extent of negotiation/consultation with workers);
(c) previous experience of technological and organisational change;
(d) the way in which the content of a job changes (job enlargement, job rotation, and job enrichment).

It is likely that the respondent's view of technological change will be affected by the overall context in which it is being introduced (for example, in an environment where there are job reductions versus one where there is dynamic job growth) and various extrinsic rewards attached to any change (such as wages). In an ideal world, researchers would like to be able to compare the experiences of workers affected by the same types of technological change to gauge how much variation there is in their job-skill profiles. Being able to ask about specific technologies is likely to lie outside the scope of many respondents' knowledge, but it may well be possible to ask questions on technological change with respect to:

(a) its scale;
(b) whether or not it is likely to replace routine job tasks;
(c) the extent to which it is different from previous technologies;
(d) how workers have been supported to acquire the skills needed to accommodate technological change (i.e. training and skill development).

There may be general interest in asking workers about technological change and other changes affecting jobs and skills, as shown in Box 4. Or there may be an interest in approaching this more directly from a skills and learning/training perspective. These types of questions are used in the STAMP and Cedefop second ESJS surveys, as the example in Box 4 illustrates; they are particularly informative, as they can give an indication of the scale of the change that has taken place and its skill intensity.

Box 4. **Questions on technological change at work**

In the last five years or since you started your main job, have any of these changes taken place in your workplace?

- Changes to the technologies you use (for example machinery, ICT systems)
- Changes to your working methods and practices (for example how you are managed or how you work)
- Changes to the products/services you help to produce
- Changes to the amount of contact you have with clients or customers (for example dealing with customer/client queries or complaints)

Source: Cedefop first European skills and jobs survey.

In the past three years/since you started your current position/since you started this job) have you started using any new computer equipment or computerised machinery?

- If yes: Now, think about the one piece of new equipment or machinery that took the longest to learn how to use. About how long would you say it took you to learn it: less than one week, one week to one month, between one and six months, six months to a year, or more than a year?

Source: STAMP survey.

[In the last 12 months IF tenure>=1 year] [Since you started your main job IF tenure<1 year], did you have to learn to use any new computer programmes or software to do your main job? By new we mean those you started using for your main job [in the last 12 months IF tenure>=1 year]. Please exclude minor or regular updates.

Source: Cedefop second European skills and jobs survey.

When putting questions to workers about the introduction of new technologies, it is important to clarify a number of issues to obtain sensible and robust answers. Careful definitions need to be provided regarding what constitutes technological change, for instance if the concept refers to new computer software, or ICT equipment or also includes computerised machinery and computerised equipment or something else. Other important survey design decisions include:

(a) specifying whether a respondent had previously used or not the specific technologies at work, in other jobs or in other life situations (for example for recreation or social purposes), or if the interest lies only in new technologies that have recently been adopted in a workplace or used as part of a worker's job;

(b) deciding whether the survey focus should include minor updates to existing technologies or if interest lies only in major episodes of change. Many estimates of technological change could be inflated as they capture minor updates to software or equipment that does not lead to marked changes in job-skill requirements;
(c) considering whether to ask directly about whether the use of new technology was also accompanied by a need for learning, signifying that it entailed a skills-augmenting element;
(d) specifying a clear and relatively recent time window (for example past 12 months, past three years) in which a new technology that could have potentially affected skill requirements was introduced.

Besides asking about technological and other changes in general terms, there may also be an interest in a specific technology, such as computers, robots and AI. Questions related to these need to be drafted in such a way that they make sense to the respondent. Not everyone, for instance, knows what an algorithm is, or what constitutes a robot or AI. The types of questions that can be asked are usually of the type presented in Box 5.

Box 5. **Question on specific technologies at work**

In the last three years, did any of the following changes occur at your workplace?
- New computerised or automated equipment was introduced into the workplace.
- New communications technology equipment was introduced into the workplace.
- Robots were introduced into the workplace.

To what extent are you familiar with the following technologies?
(a) Virtual/augmented reality
(b) Big data
(c) Artificial intelligence
(d) Internet of things
(e) Internet of services
(f) 3D printing
(g) Blockchain technology
(h) Quantum computing
(i) Other technologies

Source: Cedefop.

Information on skill levels can then be related to questions about technological change – and other types of change – in the workplace over a given period of time, and the respondent's experience of those changes.

In thinking about how to capture information on skills and technological change, the reader is referred to Cedefop's European skills and jobs survey (Cedefop, 2015; 2018). This is an exemplar employee survey, designed for the European Union, aiming to collect detailed information on a wide range of skills needed in jobs, alongside other information about changes in jobs over time and workers' experience of technological change (Box 6).

Box 6. **The Cedefop European skills and job surveys**

The first European skills and jobs survey adopted an innovative approach to collecting information on an individual worker's skills, in that it asked them about their current skills and how these have changed, and why, since they started doing the job. This provides the opportunity to look at how a range of factors have influenced the development (or not) of an individual's skills set. Detailed information on the job/occupation of the worker was also collected, alongside that on specific skills (their importance to the job and workers' assessment of how good they are at those skills).

In summary, the first ESJS survey captured information about:

- the current job (occupation in which the person is employed);
- educational attainment (highest qualification held and field of study, and the qualification level required if entering the job today);
- basic skills (workers' ratings of their proficiency with respect to various skills sets, including numeracy, literacy and ICT skills);
- change in skills since start of current job (whether skill levels have improved/worsened, whether skills have remained matched to the job, whether the worker has engaged in activities to improve skills);
- training (access to various types of training).

The survey also asked whether people have been exposed to technological change, in particular if they had been subject to changes to the technologies used (for example machinery, ICT systems) or to their working methods and practices in the recent past. Such data can be analysed to reveal how the impact of technological change, other things being equal, affects the demand for skills and, importantly, which skills are affected and whether the impact is to increase or reduce the use of certain skills (McGuinness et al. 2019). In this way policy-makers can obtain detailed information on both the specific jobs and the specific skills which have been affected by technological change (see Cedefop, 2015; 2018; Pouliakas, 2018).

To address the ongoing policy debate about the potentially enriching or destructive impact of digitalisation on jobs and the future of work, as well as heightened concerns about what may be a non-transitory, long-term impact of the Covid-19 crisis on EU job markets, Cedefop initiated the second ESJS wave in 2021.

The second wave of the ESJS collects comparative information from EU Member States (plus Norway and Iceland) and some EU acceding countries on the impact of technological change and digitalisation on workers' job tasks and skill mismatch and their readiness to adapt by investing in continuing (online) vocational education and training. Policy-relevant information on the incidence of teleworking in EU job markets, the degree to which employees have recently adopted new digital technologies, and the extent to which they have invested in non-formal and informal learning to cope also with the consequences of the coronavirus pandemic, is collected. Such information can be superimposed on the degree to which workers' job-tasks are routine or involve high cognitive requirements and interpersonal skills, building on the dedicated task module that collects information on workers' job-skill requirements. The survey also collects information on workers' perceived job insecurity due to automation and skills-displacing technological change.

Source: Cedefop: https://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-survey-esjs

In uncovering the relationship between technological change and skills, it is important to be aware of the limitations of worker surveys. Workers can report if and how they have been affected by technology adopted within their workplace, including whether technology has caused them to lose their job recently, whether it leads them to anticipate possibly losing their jobs or relevance of their skills in the next year, or if it has changed the task composition of their jobs recently. However, changes in the composition of employment can be driven by shifts in employment across establishments. If the workforce in more technologically backward establishments contracts, due to competition from more advanced establishments, it is likely that the displaced workers will be unaware of the underlying reason for their job loss.

It may also be the case that there are potential spillover effects (at industry or workplace level) due to new technologies for the individual workers, even though, in their view, technological change has not had direct impact on the part of the company in which they are based. It is reasonable for a survey to ask workers about their own workplace, but they cannot generally be expected to have detailed knowledge of other workplaces or system-level dynamics. To detect these kinds of technology-induced shifts would require data on ICT adoption or investment by industry at a sufficiently detailed level.

Table 4 provides a summary of the issues to consider when thinking about using a survey of employees/individuals to explore the link between technological change and skill levels. It provides a checklist of what needs to be considered before commissioning such a survey.

Table 4. **Issues to consider before launching an individual/worker skills and jobs survey**

Issue	Detail to be considered
Initial check	Do similar data already exist elsewhere?
Types of questions that can be addressed about technologies	• Have individuals experienced technological change in their jobs (e.g. over the past 12 months has the introduction of new technology significantly changed the way you do your job?)? • Have individuals recently used specific technologies (e.g. computers, robots, AI) in their jobs?
Types of questions that can be addressed about skills	• Rating of individuals' own skills compared with those required to undertake the job – this can be disaggregated to ask about specific skills (e.g. numeracy, literacy, ICT) • Level of specific skills • Frequency of specific skills use • Importance of specific skills for doing the job • Complexity of skills • Change in use of specific skills
Requirements	Sampling frame from which to derive a representative sample of employees/individuals in which there is an interest
Data collection steps	• Specifying hypotheses to be addressed • Specifying the variables and their relationships required to test the hypotheses • Drafting questions that will allow variables to be constructed (the questionnaire) • Crosschecking questions with other surveys (to allow for comparisons) • Design of sample (random probability, quota sampling, etc.) and sample size required for robust estimates to be derived • Type of survey (face-to-face, telephone, online, etc.) • Fieldwork • Weighting dataset to population estimates • Data cleaning
Selected further literature	• European skills and jobs survey • UK skills and employment survey • Handel, M. (2017). Measuring job content: skills, technology, and management practices. In: Buchanan, J. et al. (eds). *The Oxford handbook of skills and training.* Oxford: Oxford University Press, pp. 92-123.

Source: Cedefop.

2.3. Skills surveys: a summary

The type of information skills surveys can provide (Table 5) is not focused on the future *per se*, but can be of value in revealing the direction of change. The key point is that surveys among employers and employees can provide detailed information on how skill demands are changing in the workplace and on the drivers of change. These surveys demonstrate the way in which technological change's impact on skills is mediated to some extent through work organisation, where employers have a degree of strategic choice. It is not necessarily the case that technology x will always create a demand for skill y: ultimately the impact depends on the way in which employers decide to configure jobs (occupations) with respect to the combination of tasks they expect the employee to undertake.

Table 5. **Typical information skills surveys can provide about technological change and skills needs**

Employee skill surveys	Employer skill surveys
Information about skill content of jobs	Extent of technological change taking place in workplaces
Changes in the skill content of jobs	Impact of technological change on skills proficiency of existing employees
Impact of technological change, other things being equal, on skill content of jobs	Extent to which technological change affects recruitment from external labour market (skill shortages)
Information on workplace factors that have some bearing on the impact of technological change on skill content of jobs	Whether technological change is supported by reskilling and training of employees
Understanding the role of training in mitigating the impact of technological change on skills	

Source: Cedefop.

There are difficulties in asking questions about the future in questionnaire surveys; this is especially so for surveys among workers who may not be well placed to provide an informed view about future developments, other than those their employer has told them about. In employer surveys there is evidence suggesting future technological changes may be underestimated. Surveys are generally much better at delivering information about recent changes and the current situation.

Healthy scepticism of studies that claim to discern the future by asking respondents what changes they anticipate in their jobs or firms in the next five or 10 years is appropriate. A good principle of survey research is to avoid asking people questions they are unable to answer, or at least answer reasonably easily. Some of the risks in asking people to imagine future conditions can be illustrated by the World Economic Forum's (WEF) *Future of jobs* survey, which surveyed chief human resources and chief executive officers in leading global employers from November 2017 to July 2018, regarding their current planning and projections related to jobs and skills in the period leading up to 2022 (World Economic Forum, 2018). Among the results for the adoption of ICTs:

(a) 36% of executives thought it likely or very likely their company would adopt quantum computing in the next five years;
(b) 23% anticipated adopting humanoid robots;
(c) 41% thought it likely they would adopt 3D printing;
(d) 45% anticipated adopting blockchain technology (World Economic Forum, 2018).

Although the anticipated adoption rates for more mundane ICTs were more plausible (for example 72% expecting to adopt cloud computing), it is clear that particular types of respondent given room to use their imagination regarding the future, will do exactly that.

A less extreme example of this problem occurred when the US Census Bureau conducted the *Survey of manufacturing technology* (SMT). In 1988, the SMT asked plant managers about the presence of 10 automation technologies and their plans for implementing them in the following five years if they did not use them currently. When the next (and final) wave of the survey was conducted in 1993, actual prevalence rates for most of these technologies were 10 to 12 percentage points lower than the rates implied by the responses to the intend-to-implement questions asked five years earlier (Handel, 2004). Clearly, both the WEF and SMT surveys exhibit a significant bias toward overstating the prospective rate of technological change over a five-year period, suggesting moderate to serious problems with validity.

In contrast to these requests for medium-term speculations from respondents, it is useful in terms of technology forecasting and skills anticipation to ask workers whether they have concrete knowledge of technological or other changes in their workplace or the broader labour market in the next 12 months, that are likely to affect job security, required skills, or other relevant outcomes in foreseeable ways.

In relation to technological skills obsolescence and its impact on employment, longitudinal data are needed to demonstrate how technological change affects skill demand in a particular workplace or the chances of a worker remaining in employment. To date, these types of data are scarce, mainly because of the costs involved in carrying out panel studies and the problems attached to sample attrition over a relatively long period of time. The construction of pseudo-cohorts within a survey can alleviate this to some extent, but the results will be dependent upon the recollection of respondents. For example, it is possible to construct a survey of people of different ages who are economically active and ask them about their recent employment history (career history).

When deciding to carry out skills surveys, key questions to address are why the survey is needed and if there is an existing survey that already provides the data. This may seem obvious, but there has been a proliferation of surveys over recent years such that would-be respondents may face survey fatigue. This can be especially true for employer surveys where those workplaces which meet certain criteria – typically large ones which employ many people – are relatively few and therefore tend to receive multiple requests for information.

Skills surveys should also ensure that the respondent is able to answer the questions on technological change and skills easily. Speculative and prospective questions, or those on generic types of technologies (for example artificial intelligence) that some individuals or human resource managers (especially in small and medium-sized businesses) are unaware or imperfectly aware of, may give rise to unreliable data collection.

CHAPTER 3.

Technological change and skills forecasting

3.1. Modelling technological change

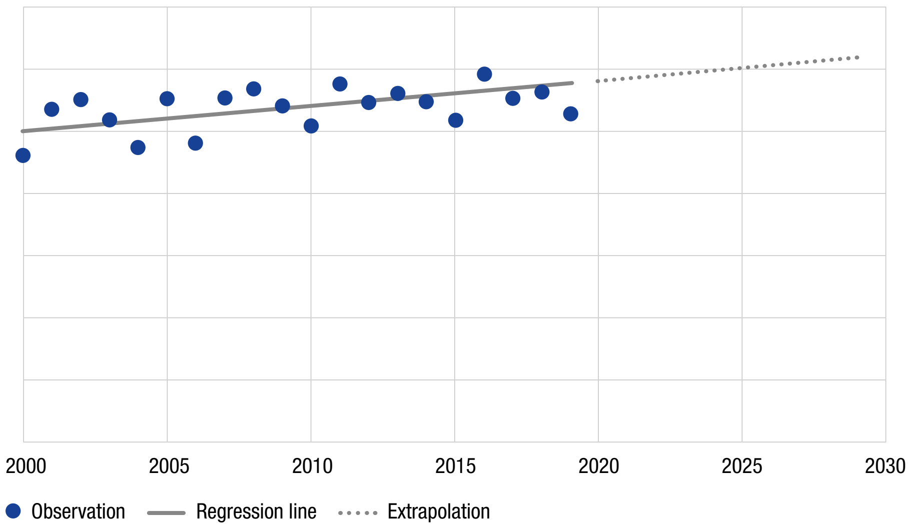
Skills forecasting involves the use of relatively elaborate economic models that provide insights into future developments in the structure of employment, skills supply and demand. This is usually derived from economic relationships in time series analysis. Said simply, forecasting can be thought of as extending trend lines.

Figure 1 provides a stylised extrapolation of the future based on the past. Past observations, depicted as dots, can be analysed using approaches such as regression techniques, which allow the establishment of relationships, in this case, over time. The outcome variable could, for example, be employment levels (in an economy, sector, or occupation). If a relationship is consistent over time, it can be extrapolated into the future, depicted by the dotted line. This will work as long as the identified relationships continue into the future without any structural breaks or shocks ([5]).

If the possibility of technological change is introduced, which is not part of the model, the underlying relationship based on which the original forecast is made might no longer hold. Figure 2 shows how the prediction after technological change may lead to higher (or in some cases lower) general levels of the outcome variable of interest. Technological change might even speed up the employment effect (affecting the slope of the line), while in other cases the impact might be temporary or wear off after a period of time (Figure 3).

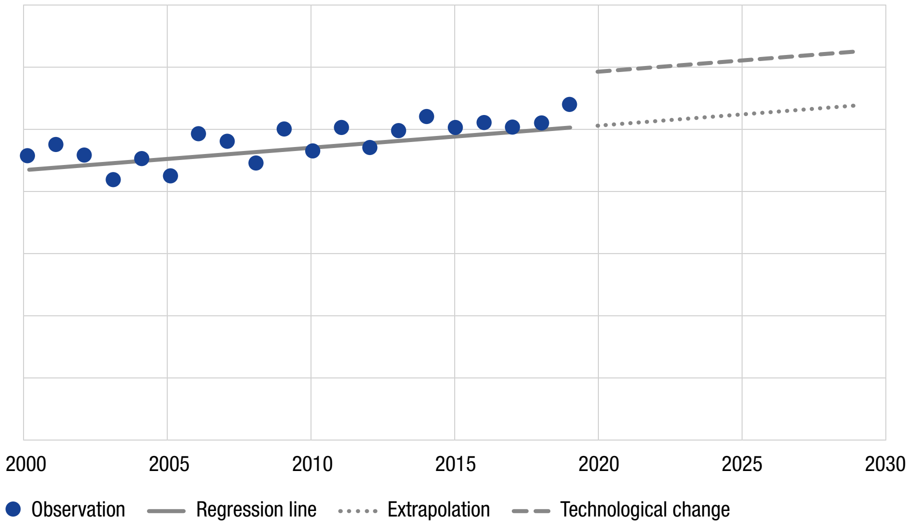
([5]) This simplistic version should be seen as representative of many estimated relationships between one or more variables that can be either consistent or evolving over time. An important requirement is that there is no structural break or shock to the relationship (or to the underlying data) for the forecast to continue to hold with some degree of accuracy.

Figure 1. **Stylised extrapolation of future trend**



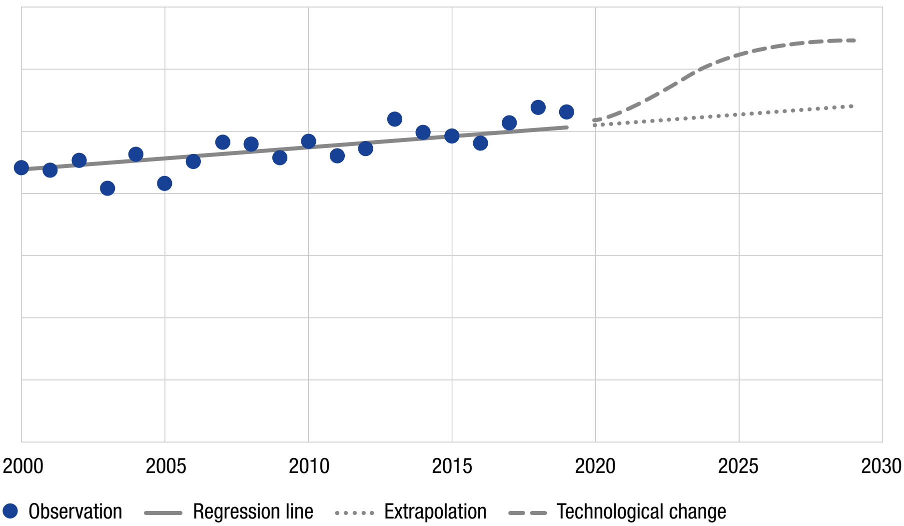
Source: Cedefop elaboration.

Figure 2. **Stylised extrapolation of future trend with technological shift**



Source: Cedefop elaboration.

Figure 3. **Stylised extrapolation of future trend with dynamic changes**



Source: Cedefop elaboration.

Any analysis of technological change in the context of skills forecasting poses the following challenges:

(a) need to identify that there is a new technology that affects the development of the variable of interest over time (the 'relationship');
(b) uncover the way technology affects the estimated relationships (is it a shift, as in Figure 2, or is it an increase of dynamics as in Figure 3?);
(c) describe the process whereby technology affects estimated/underlying relationships in the model (does the effect continue over time? Does it slow down or diminish?).

Even with an identifiable technology and understanding of the way it affects specific relationships, estimating the influence of the technology in the future can still be challenging. The main problem for the forecasting process is a need for observations over time; in many cases there are no historical data and the influence and importance of technology only becomes apparent ex-post, which may be too late from a skills anticipation perspective.

3.2. Modelling skill demand

Quantitative modelling approaches to anticipating future skill needs include:
(a) univariate models, such as simple extrapolation of past trends (mechanistic techniques) and more complex time series methods;
(b) complex multivariate time-series-based behavioural/econometric models.

Extrapolation techniques are often used when only very limited time series information is available, which clearly restricts the sophistication of the analyses. Where longer time series of observations are available, more complex analysis may be possible; here, replicable patterns in a time series may be found and used to predict its future path. Such approaches are widely used in the business and financial world, though they are much better at predicting short-term change than longer-term patterns. Unfortunately, most linear (or more complex) trend patterns eventually come to an end (trends bend) in their ability to predict the true developments over a longer time. Therefore, they should not be relied on for medium- to long-term forecasting.

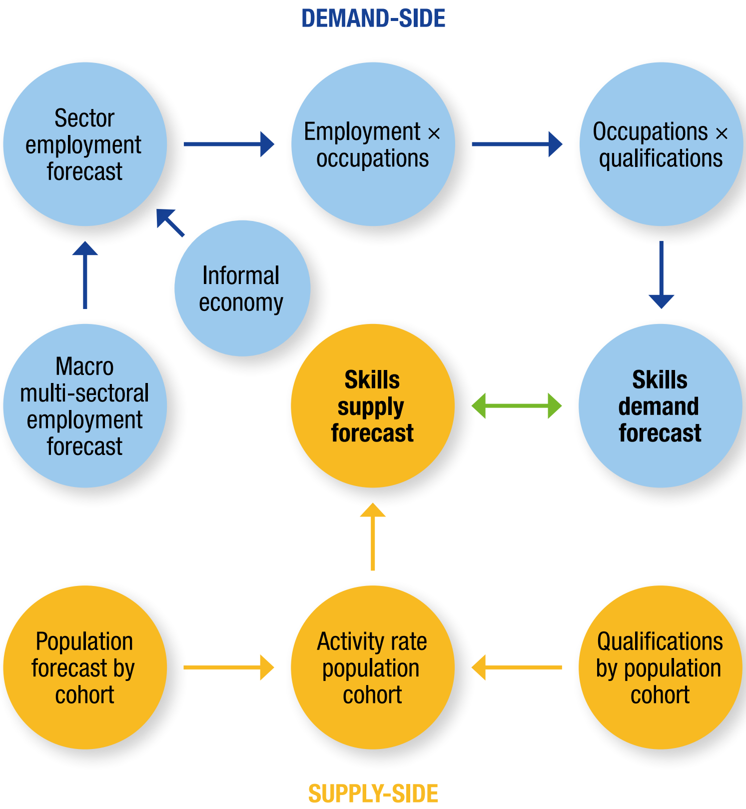
The typical quantitative modelling approach involves two key elements. The first key component is a multisectoral macroeconomic model of some kind – usually built around a Leontief input-output table – that takes into account the interlinkages between sectors. Such models are usually estimated using complex econometric methods, although computable general equilibrium (CGE) models (where parameters are imposed rather than estimated) are also used. Most skills forecasting is carried out using econometric models.

Econometric models are subsequently built using sophisticated statistical and econometric techniques, and using large datasets drawn from official sources, including national accounts and estimates of employment based on employer and household surveys. A typical multisectoral macroeconometric model comprises many equations. Parameters are estimated using multivariate econometric techniques, based on error-correction and related time-series methods or Heckman correction methods on cross-sectional data.

The model typically has two main components:
(a) a demand for skills module;
(b) a supply of skills module.

Figure 4 presents the modelling framework, showing where the supply and demand components meet.

Figure 4. **Modelling framework underlying skill forecasts**



Source: Cedefop elaboration.

The key steps in skills forecasting are common and typically include:

(a) a projection of employment prospects in the main sectors or industries;
(b) translation of these projections into trends in employment at the level of occupations;
(c) an assessment of replacement needs (to take account of job openings arising from retirements and other withdrawals from the workforce);
(d) forecasts of supply of labour by age, gender, qualification level and occupation, encompassing both new entrants to the workforce and the unemployed;
(e) calculation of (future) labour market imbalances by comparing occupational demand with various indicators of supply.

3.3. Advantages of skill forecasts over alternatives

The main advantage of the macroeconomic modelling approach to skills forecasting is its simplicity (if a macroeconomic model already exists). It is essentially a method enabling the disaggregation of an existing macroeconomic employment forecast and identification of the implications for skills demand in a relatively quick and easy manner. Similarly, on the supply side, demographic forecasts can be used to predict what the future holds for working age population numbers and their respective qualifications.

In general, quantitative skills forecasting models should be used to make projections because they:

(a) make assumptions about the future explicit and transparent;
(b) enforce systematic and logical thinking;
(c) act as a focus for intelligent debate ([6]);
(d) provide a useful counterfactual (to anyone interested in possible future outcomes) against which to assess policy impacts (i.e. what would have happened in the absence of a policy intervention).

They should not be relied on for detailed employment planning or to give precise indications of education and training requirements, as the extrapolations are necessarily simplified and cannot identify exact numbers.

Most reviews of international best practice in skills forecasting suggest that the use of a national multisectoral macroeconomic model-based approach is the preferred option ([7]). Such models are regarded as essential in order to obtain a robust and consistent sectoral employment scenario, which is the starting point for any comprehensive assessment of changing technologies and skill needs.

The advantages of such a multisectoral approach are:

(a) the sectoral and other detail such a model provides;
(b) the fact that it is typically comprehensive, covering the whole economy;
(c) logical consistency;
(d) imposition of accounting constraints;

([6]) Forecasts should not be seen as an end in themselves but rather as a focus for informed debate. They are a considered view of what might happen next. Without some kind of firm statistical foundation, all such debate is mere speculation.

([7]) See ETF et al., 2016a; 2016b and 2016c.

(e) recognition of economic constraints and influences;
(f) the fact that it helps make underlying assumptions explicit;
(g) provision of consistent scenarios across all sectors.

Different macroeconomic forecasts for employment can, in principle, also be compared for their implications for skills demand, as can different population projections. In addition, changes can be made to model assumptions, such as the proportion of different occupations across sectors, or qualifications in occupations, to see what difference this would make to the overall findings.

As with any skills anticipation method, macroeconomic forecasts also have disadvantages, limitations and problems. These relate to:
(a) technical limitations, within fixed resource limits ([8]);
(b) limits to current understanding of the way labour markets work;
(c) the possibly limited relevance of the past (such models being based on assuming continuation of past patterns of behaviour). This may be a pronounced issue in the context of countries subject to significant political and social disruption;
(d) resource costs of development and maintenance ([9]).

The data requirements of quantitative modelling approaches are substantial. They include a sufficiently long time series of consistent data on a range of economic and labour market indicators (especially on employment, skills, and labour supply), as well as input-output tables. Sectoral employment data lie at the heart of any multisectoral modelling approach to assessing changing skill needs. Ideally such data need to be linked to other economic indicators within a system of national accounts ([10]). Developing the necessary data infrastructure requires many years of substantial investment.

There are also limitations arising from the simple fact that often the data used to build models were not collected with modelling in mind:

([8]) With unlimited budgets, much better data can be collected, and better and more complex models can be built, but there are limits to our understanding, so there is no guarantee these models will be able to predict the future any better than simpler models.
([9]) These costs include those directly concerned with building and executing a skill forecasting project. This is distinct from the statistical infrastructure necessary to support such activity, which requires a much more long-term commitment. The former is modest compared to the latter but can still be substantial.
([10]) A fully specified multisectoral macro model requires a large amount of economic and labour market data on each sector.

most economic and labour market data support tax collection and other government/administrative objectives. They are rarely, if ever, collected with the objective of being able to build economic or other models to be used specifically for skills assessment and forecasting.

A forecast model needs to be based on a number of macroeconomic assumptions to make it operational. This includes explicit assumptions, such as population forecasts by cohort, as well as more subtle assumptions, such as the use of shares of the informal economy.

With simplicity, however, comes limits. Because the modelling system is effectively a top-down approach, it cannot deal with more complex, sector or policy-specific questions that require a more bottom-up methodology. It is important to start with a relatively simple framework, so that understanding and knowledge can be established as a base upon which to build more complex representations of the economy. The main contribution of using a model-based framework to reflect on the demand for and supply of labour is that it enables establishing a baseline of skills profiles and trends. It is crucial to keep in mind that any image of the future, as sketched by models, is limited by the nature of their construction.

Quantitative models should not, therefore, be seen as a panacea for understanding the future of jobs and skills. Nevertheless, in most of the countries that conduct regular national assessments of future occupational and skill requirements ([11]), such models are regarded as an essential cornerstone. Quantitative modelling is increasingly being adopted in developing, as well as developed, countries, as data availability and the capacity for model building improves ([12]).

3.4. Incorporating technology in a skill forecasting modelling framework

As the estimated relationships within the macroeconomic model rely mainly on historical data, and the assumption is made that they will apply in the future, this also implies that only technological changes or technologies already present can be expected to be identified and included in the modelling relationships.

([11]) This includes most members of the OECD and the EU.
([12]) For a review see, for example, ETF et al., 2016a; 2016b and 2016c.

Including technology or technological change that affects the labour market, and through it the skill mismatch outcome, faces certain problems. As identified, traditional skills forecasting methods presume past experience will extend to future developments. To include technology which is not yet incorporated into the modelling framework, an analyst would need to consider key steps.

First, the technology that can impact future needs has to be identified. This is necessary especially if the technology has an impact that cannot be anticipated from its past development. Technologies that evolve over time, for which past development is a good measure of future developments, may be captured well within quantitative models. The problem arises if the technology is new, if it is evolving at a speed not anticipated, or is impacting parts of the economy previously unaffected by it. An assessment must be made about whether the new technology comprises a structural break. Important questions to be asked include: what occupations or sectors are most likely to be affected by such new technological developments? Will it spill over into new, yet unaffected areas within the anticipation period?

Second, the areas in which the technology affects the model need to be identified. This can be done within the macroeconomic model, affecting both supply and demand components, overall economic growth, sectoral employment changes, and also the consumption side. It can affect the occupational structure within sectors, as technology might change the production process of goods and services in such a way that, for instance, more automatisation encourages a shift from intermediate level production workers towards higher-level engineering. However, there can also be lateral substitution through technology from one type of occupation to another.

Third, it is necessary to gain insight into the dynamism of the technological development. In short, what is the speed of development and its impact on the labour market and skills for the period of anticipation? The speed of these changes usually cannot be identified from the past, as they depend on patterns of technology adoption and the diffusion of work practices that are not easily known or estimated.

In summary, including technological changes into a skill forecasting model is challenging. Dedicated data sources that can identify technological change are typically lacking. Such gaps are usually overcome by relying on a combination of qualitative and quantitative evidence, coupled with assumptions used to estimate impacts on employment and skills demand. A much-debated early attempt to identify changes in occupational demand due to technological change by Frey and Osborne (2017) is discussed in Box 7 ([13]).

Box 7. **Extrapolating future skill demand based on external evaluations of technological change**

The well-cited study of Frey and Osborne (2013; 2017) provides an estimate of the degree to which occupations may be replaced by automation. The basis for this prediction is expert evaluations of the possibility of replacement of machine-learning algorithms for labour in a specific subset of all occupations. These evaluations (a training data set) were then extrapolated using specific aspects of occupations linked to their task features and suitable non-parametric regression techniques.

Based on the extrapolation, an automation probability was derived. While the combination of expert knowledge on the degree to which specific occupations might be automated seems sensible, the approach remains one-sided: it only provides an estimate of how much a task or job can be automated. It does not, however, take into account the economic feasibility of this actually being done – which can be a cost and employer incentives question (Cedefop, 2020) – as well as the equilibrium effects of such automation. It is likely that additional work will be generated following machine replacement, given that the overall output is produced more cheaply, or that different tasks are required; both could lead to additional employment effects.

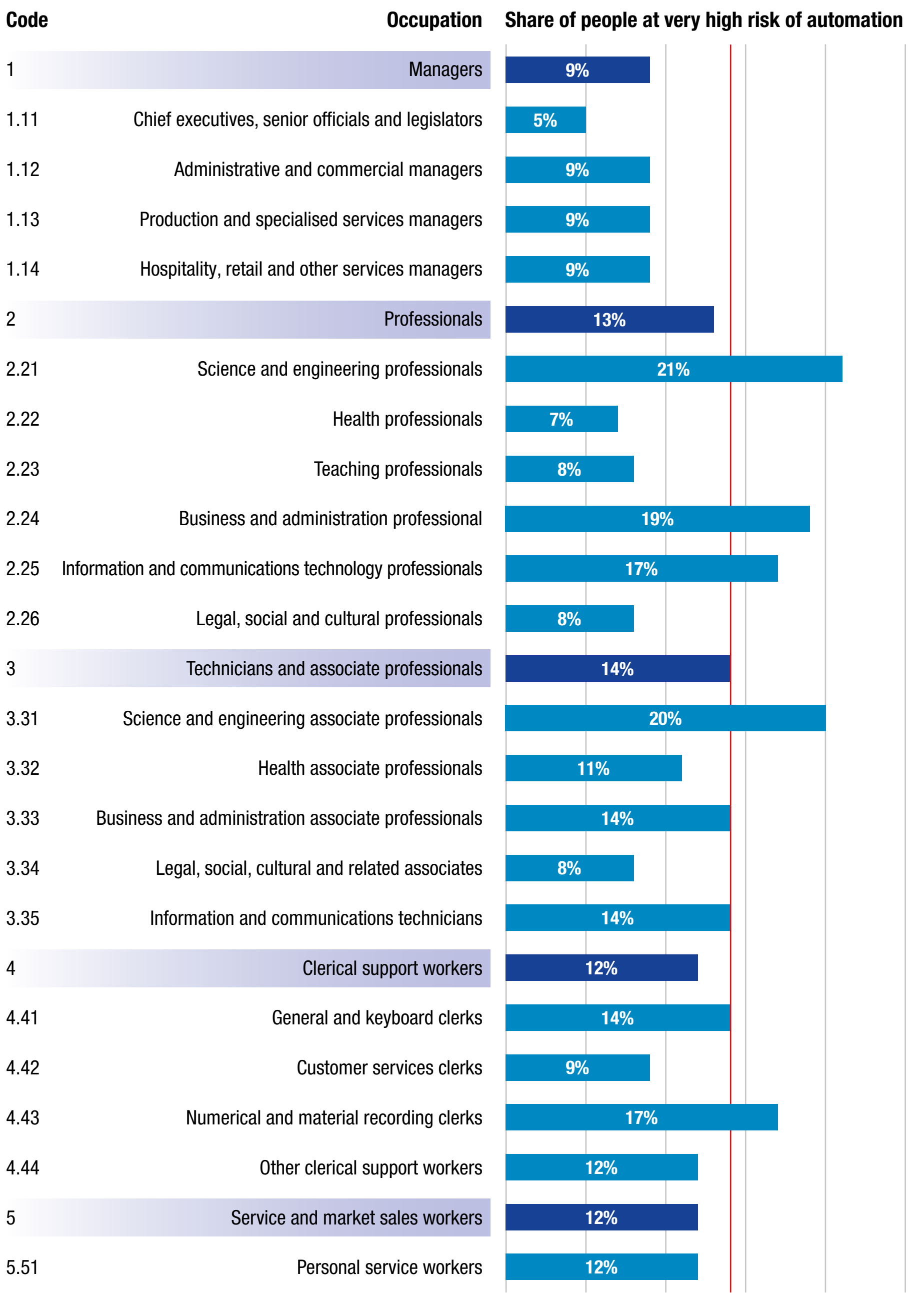
Other studies on the effects of automation on the occupational structure have tried to take some of these secondary effects into account. Using data on tasks and skill needs in jobs, collected in Cedefop's European skills and jobs survey, Pouliakas (2018) estimates the empirical relationship between the variance in skill needs within occupations and the probability of automation, on the basis of which jobs are classified according to their estimated risk of automation. A job is considered as subject to a very high risk of automation when the median automation probability estimated exceeds 70%. The number of jobs by occupation at high risk of automation in the future can then be estimated by superimposing the share of people working in the high-risk occupations onto the occupational projections derived from an external skill forecasting exercise (Figure 5).

These approaches are partial and non-endogenous: without considering the supply-demand interactions in the macroeconomic model, effects can be difficult to estimate. This becomes even more of a challenge as skills forecasting in many countries relies on increasingly complex macroeconomic models, making updating of relevant estimations to model technological changes properly a complex and demanding exercise.

Source: Cedefop.

([13]) While the study was published in 2017, initial versions circulated in 2013.

Figure 5. **Occupations at risk of automation in the period to 2030**



Code	Occupation	Share of people at very high risk of automation
5.52	Sales workers	14%
5.53	Personal care workers	6%
5.54	Protective services workers	14%
6	Skilled agricultural, forestry and fishing workers	16%
6.61	Market-oriented skilled agricultural workers	16%
6.62	Market-oriented skilled forestry, fishery	13%
6.63	Subsistence farmers, fishers, hunters and gatherers	18%
7	Building, crafts or related trades workers	21%
7.71	Building and related trades workers	19%
7.72	Metal, machinery and related trades work	22%
7.73	Handicraft and printing workers	25%
7.74	Electrical and electronic trades workers	18%
7.75	Food processing, wood, garment and related workers	22%
8	Plant and machine operators and assemblers	19%
8.81	Stationary plant and machine operators	23%
8.82	Assemblers	22%
8.83	Drivers and mobile plant operators	16%
9	Elementary	16%
9.91	Cleaners and helpers	10%
9.92	Agricultural, forestry and fishery labourers	19%
9.93	Labourers in mining, construction, manufacturing	20%
9.94	Food preparation assistants	13%
9.95	Street and related sales and service workers	8%
9.96	Refuse workers and other elementary workers	18%

NB: The red line represents the average value of automation risk in the EU.
Source: Estimates of Pouliakas (2018) superimposed on Cedefop skill forecasts.

In essence, technological change can be included in macroeconomic models by either explicitly modelling the change process or by adjusting assumptions (often parameters) and relationships in the model, often based on qualitative insights (Box 8). Technological change, especially in its productivity-enhancing element, is regularly included in models. The resulting higher productivity can also be observed from monitoring statistical data over time. By developing the relationships that pick up and model the impact of technological change, more insights can be gained by varying the implied relationship (i.e. sensitivity analysis). For example, if there is an expected shift in the productivity-enhancement effect of a new technology, the increase in productivity could be captured by the model by integrating such an expectation.

Box 8. **Combining qualitative and quantitative inputs in the German forecast**

In the German forecast up to 2030, a digitalisation scenario was developed, based on qualitative in-depth studies on specific aspects of digitalisation and automation. Besides the baseline scenario, an accelerated digitalisation scenario was developed to assess the impact of increasing digitalisation on the labour market. The qualitative studies provided necessary inputs for altering assumptions within the macroeconomic model at the sectoral level, leading to changes in demand for occupation and skills within sectors.
In many instances, lack of historical data on the effects of changes had to be overcome by including information from the qualitative studies. The qualitative information had to be translated into quantitative estimates that could feed into the macroeconomic model, i.e. sector-based employment effects, and into changes of the occupation and/or qualification effects of digitalisation. Some of these were ad hoc and expert-based, while others could be grounded more in the information the qualitative studies provided.

Source: Cedefop.

Occupation and qualification forecasts, which build on sectoral forecasts, also rely on identifying historic developments that are expected to continue in the future. Digitalisation and technological change potentially affect work organisation within sectors. As long as these changes can be identified and occur gradually as time passes, they can be included in the occupation and qualification modules of the skills anticipation model. Trends that occur rapidly, that have no precedence or follow a pattern that is difficult to predict, are much more difficult to incorporate. As in technology adoption models, attempts can be made to model the speed of change. However, the identification of these relationships is usually well beyond the scope of what can be achieved in modelling, and data are usually insufficiently detailed and reliable to fit 'technology-adoption' types of models.

Another problem is the emergence of new occupations or skills that are neither classified in the statistical data nor existed in the past. The web-developer occupation did not exist before the 1990s, and the growing employment in this field and trends in associated skills and qualifications were initially picked up only in related occupations, given that these positions were filled by people with qualifications suitable for the tasks to be performed.

Given that technological changes are difficult to estimate and identify using past data, in many cases model builders rely on using multiple, partial sources to adjust assumptions within the model. To identify the impact of these changes, running and forecasting different scenarios is currently the best available approach to identifying labour market changes implied by technology and digitalisation.

3.5. Limits to skill forecasting with technological change

While skills forecasting can provide useful insights by combining historic trends to shed light on current and likely future developments of skills supply and demand, it falls short when new developments occur that cannot easily be identified and included in models representing economic relationships. The identification of emerging or future technological change is crucial to its inclusion in such models. But, as the methods have their foundation in historic developments, they tend to miss predicting outcomes that are entirely novel, skills that have not been used in the past, or occupations that are yet to be defined. Methods that complement skills forecasts models, such as big data, foresight and other types of skills anticipation, are increasingly used to shed some light on likely future trends driven by technological change.

Table 6 provides a summary of the issues to consider when thinking about engaging in the econometric forecasting of skill needs in relation to technological change. It provides a checklist of what an analyst will need to consider before commissioning or engaging in a modelling exercise.

Table 6. **Issues in developing a skill forecasting approach to the impact of technological change**

Issue	Detail to be considered
Initial check	• Can existing skill forecasts be extended to include technological change? • Is the technological change sufficiently identified and measurable using data from the past?
Types of questions that can be addressed about technologies	• What is the impact of technological change on labour demand and supply? • How do different speeds of technology adoption in the workplace (as seen in scenarios) affect the economy differently?
Types of questions that can be addressed about skills	• What is the impact of various external factors, such as technological change, on the demand for skill (typically using occupation and highest qualification as proxy measures of skill)? • What are the estimated replacement demands as well as the overall change in the number of people employed in an occupation?
Requirements	• Macroeconomic model with the possibility to include/model technological change at the macroeconomic and sectoral level • Detailed microeconomic data on employment by sector/occupation/skills • Detailed data series on technological change
Modelling steps	• Run the model without specific modelling of technological change • Determine technological change scenarios • Determine within the macroeconomic model how (different assumptions on) technological change determines model parameters; if necessary, re-estimate relationships that might be affected by technological change • Determine within the occupation/qualification modules how technological change affects the assumptions, speeds of adjustment and job requirements • If necessary, adjust assumptions/modelling of replacement needs • Ensure realistic assumptions including supply/demand relationships and interactions
Selected further literature	• ETF et al., 2016b: Developing skills foresights, scenarios and forecasts • Cedefop: Skills forecasts

Source: Cedefop.

CHAPTER 4.

Choice of method

In this first Cedefop guide on methods for identifying technological change and its impact on skill requirements, consideration has been given to what may be referred to as conventional labour market intelligence approaches. This includes employer and employee surveys to collect information about changing skill needs, and using skills forecasting to provide an indication of projected future changes.

Major investments in skills anticipation over the past 20 years have prepared the groundwork for anticipating future skill demand. Significant advances have been made in capturing detailed information about how people's jobs are changing in the face of numerous shifts in what goes on in the workplace. Surveys, such as Cedefop's European skills and jobs survey and the OECD's survey of adult skills, for instance, now provide detailed information on the skills required in jobs and how these skills have developed or changed in the recent past. Improvements in the econometric forecasting of future skill needs have helped provide a more detailed view of the future than was available at EU and Member-State levels at the time when skills forecasting became widely used.

More recently, the use of big data and AI-driven techniques has supported developing granular data on skills and technologies that would have been unimaginable 20 or 30 years ago (see Cedefop's second practical guide referred to in Section 1.5). These techniques have been used to harvest data from, among other sources, vacancy websites, patent and scientific paper databases, to give a previously unprecedented amount of detail on emerging technologies and skill needs.

Databases of online job postings or other similar web-sourced data have especially become a rich source of information on job skill requirements and they are anticipated to become increasingly important in research going forward. But they will not eliminate the need for surveys designed to address specific research questions. The reasons are that the underlying data extracted from web sources are unstructured and not generated for research uses. As a result, any repurposing, or data classification and analysis carries uncertainties and limitations. Another major problem is the issue of representativeness. For instance, online job portals do not cover many vacancies filled through word of mouth. Representativeness varies by occupation and coverage of different labour markets tends to be linked to data source type (for example high-skilled jobs in private web portals and blue-collar jobs in public employment service portals). Based on flow data, it is not clear whether vacancy postings are representative of the current stock of employment with respect to skill requirements; jobs with above-average turnover will be overrepresented relative to their share of employment. Single posts can represent multiple vacancies, or even no vacancy, given the low cost of online job listing and employers may post jobs online simply to see which potential candidates are available on the labour market (so-called 'ghost' vacancies, see Cedefop, 2019).

There are also challenges with the skills information itself collected in web-sourced data. A survey will use a common set of questions to all respondents in the universe and score responses on a common scale, while online job ads will tend to focus primarily on occupation-specific skills rather than transversal skill concepts. These skills can be quite specific and difficult to aggregate into a broadly applicable, common scale because they are qualitatively diverse and usually not easily mapped into a level of complexity framework, as is typically done in surveys employing a job-skill requirements approach. It is possible to code the presence or absence of a specific skill requirement (for example commercial truck driver's license, strong problem-solving skills, biochemistry, work with robots), or count the number of skills of a given class (for example ICT-related skills) as they appear in job ads (for example the number of computer programmes required). Yet job advertisements typically may not specify all important skills and technologies explicitly; many are widespread and implicitly expected. Most online job advertisement databases also have little data on the characteristics of workers actually hired to fill jobs, which may differ from employers' stated preferences in job ads, for instance in terms of education credentials, experience, and specific skills.

Also, the algorithms for scraping and processing online postings and similar web-sourced data sources evolve, so trend studies will need to distinguish real change from statistical artefacts. By contrast, surveys can be repeated following standard procedures.

While the value of conventional labour market and skills intelligence approaches will remain and should be used as first resort when the aim is to obtain methodologically sound empirical technology and skills relationships, it is nevertheless clear that the volume of data on future skill needs extracted from other sources has improved immeasurably and will continue to do so. In many respects, the challenge is to make effective use of the wide variety of data available (an embarrassment of riches). Technology skills foresight (discussed in guide 3 of the series) also has a key role to play in making sense of information. Its key strength is analysing and critically assessing various scenarios of the future to inform policy. Implicit within the foresight process is its focus on policy-making. The strength of the foresight approach is a weakness at the same time. In some cases, a normative element that is too concerned with actively shaping the future rather than passively accepting what it will be is overly dominant.

Participatory and quantitative, non-participatory methods are not mutually exclusive. Ideally, they should support one another so that they can potentially form an iterative process, whereby the participatory process of stakeholder engagement can shape data collection and analyses in the non-participatory ones (and vice versa). Such interaction makes it possible to develop views on how the future will unfold and how informed skills policies and actions need to develop. It provides those with a responsibility for skills anticipation in a technological turbulent world with the means to ensure that skills supply does not only meet demand but does so in a way that is considered optimal and in line with policy priorities.

Table 7 provides a summary to guide policy-makers and analysis in understanding when to use the approaches covered by the short Cedefop 'how-to' guides (see Section 1.5). To learn more about big data and foresight approaches, readers are referred to the other two guides.

Table 7. **A menu of skills assessment and anticipation choices**

Type of approach	When to use	Capacity to predict the future	Timeliness
Quantitative, non-participatory approaches			
Surveys and other primary data collections	When there is a relatively well-developed understanding of the technologies and associated skills of interest. Surveys will tend to provide information on the extent of use of skills and technologies, extent to which skills are available, efforts taken to fulfil skill needs, etc.	Tend to be good at collecting information about recent past and impending changes. Not well suited to anticipating future technological changes and future skill needs.	Can be time-consuming to undertake – design of questionnaires, conducting fieldwork, cleaning data, producing findings.
Skills forecasting	Where time series data are available on skill needs (based on qualification and occupation), and where there is an underlying macroeconomic model that can provide robust estimates of future employment demand by sector, skills forecasts can provide a robust means of providing quantitative projections of future skill demand (circa 10 years ahead)	Skills forecasting models tend to provide a projection of future demand, based on an extrapolation of past trends and/or current policy. The assumption is that the future is based on a continuation of current trends. Scenarios provide some basis for varying this to some extent, to account for continual technological change.	If the model already exists, analysis can be undertaken over a relatively short space of time. But setting up the initial model and ensuring regular updates of the results can be time-consuming and resource-intensive.
Big data analysis	Particularly useful where views about the future may not be well developed: where there is uncertainty about either the types of technology that are likely to become dominant or commonplace, and/or the skills associated with those technologies. Can also provide the detailed level of analysis that forecasting and surveys struggle to provide.	Can provide relatively real-time information on technological change and skill needs. By identifying those technologies that are at the point of take-off, there is scope to gauge likely future skill needs. There are uncertainties about how representative data are of a given population and about how much 'noise' can be removed from any analysis or their inability to provide standardised information on skills complexity.	Can be time-consuming to develop initial search algorithms, but once established can be undertaken in a relatively fast manner. It needs to be borne in mind that coding/classifying of technology and skills data can be time-consuming. Maintenance and operational costs are also non-trivial.

Type of approach	When to use	Capacity to predict the future	Timeliness
Participatory approaches			
Technology foresight	Where there is a large amount of information that needs synthesising to develop actions to ensure that skills needs, associated with particular technologies, can be met. Where there is limited data and information and where expert groups can address the lack of information.	Can provide a view of the future and, importantly, an indication of how the future might be shaped for the benefit of society as a whole. Is dependent upon the availability of expert groups who can provide key input and a process in place to develop a degree of consensus about the future direction of change.	Depends upon the scale of the exercise. Full-scale foresight involving a large number of participants is likely to prove time-consuming. But it is possible, and at times advisable, to conduct foresight with smaller groups over a relatively short-time span.

Source: Cedefop.

Acronyms

AI	artificial intelligence
CATI	computer-assisted telephone interviewing
Cedefop	European Centre for the Development of Vocational Training
CGE	computable general equilibrium
DOT	Dictionary of occupational titles
ESJS	European skills and jobs survey
EU	European Union
ICT	information and communications technology
IoT	internet of things
ISCED	international standard classification of education
ISCO	international standard classification of occupations
LMSI	labour market and skills intelligence
OECD	Organisation for Economic Cooperation and Development
PIAAC	programme for the international assessment of adult competences
SMT	Survey of manufacturing technology
STAMP	skills, technologies and management practices survey
STEP	skills towards employment and productivity
VET	vocational education and training
WEF	World Economic Forum

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EN

Understanding technological change and skill needs

Skills surveys and skills forecasting

The world of work is being impacted by a fourth industrial revolution, transformed by artificial intelligence and other emerging technologies. With forecasts suggesting large shares of workers, displaced by automation, in need of upskilling/reskilling, the design of active skills policies is necessary.

Conventional methods used to anticipate technological change and changing skill needs, such as skill surveys and forecasting, have limited scope to provide insights into emerging trends. With the increasing use of big data and AI methods, analysts have new 'real-time' tools at their disposal. Skill foresight techniques are also increasingly used to gauge in-depth stakeholder information about future technologies and skill needs.

A series of short Cedefop guides aims to inform analysts and policy-makers about available skills anticipation methods used to navigate through the uncertainty of changing technologies and skill demands. This first practical guide focuses on conventional skills intelligence methods of surveys and forecasting.

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