

Getting Skills Right

Mapping Skill Shortages in OECD Countries

New Evidence from the Updated Skills for Jobs Database



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FOR JOBS DATABASE

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Foreword

Tackling skill mismatches and skill shortages is a major challenge in the context of rapidly changing skill needs. In most countries, a substantial share of employers report that they cannot find workers with the skills their businesses require. At the same time, many graduates struggle to find jobs that match their qualifications.

In light of these challenges, the OECD has developed the Skills for Jobs Database to provide harmonised data on occupational and skill imbalances that enable cross-country comparisons and support policy co-ordination in labour mobility and talent development. The database was launched in 2017 and updated again in 2022, making this the third edition of the Skills for Jobs Database. This third edition is particularly relevant, as it analyses how skill needs have evolved following recent disruptions such as the COVID-19 pandemic and the rapid acceleration of AI adoption.

This work feeds into the OECD's extensive programme of work on skills, including the Getting Skills Right series, the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills and related analyses in the areas of skill shortages, skill mismatches, work-based learning and future readiness. This report describes the method behind the *OECD Skills for Jobs Database 2026* and presents country estimates of occupational imbalances and skill shortages.

The work on this report was carried out by Marcela Veselkova and Isabel Skak Olufsen under the supervision of Glenda Quintini from the Skills and Future Readiness Division of the Directorate for Employment, Labour and Social Affairs. The report has benefited from helpful comments provided by Patricia Navarro-Palau, Michele Tuccio, Andrea Salvatori, Arthur Felix and Blanca Jimenez Vicente. The analysis benefited from data guidance from Pascal Marianna. Analysis for Australia, Canada and New Zealand would not have been possible without data shared by the Australian Bureau of Statistics, Statistics Canada and the Ministry of Business, Innovation and Employment in New Zealand.

Abbreviations and acronyms

	Refers to
AI	Artificial Intelligence
EURES	EUROpean Employment Service
HP	Hodrick-Prescott
ICT	Information and Communications Technology
ILO	International Labour Organization
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
OJP	Online Job Postings
O*NET	Occupational Information Network
PIAAC	Programme for the International Assessment of Adult Competencies

Executive summary

Labour shortages reached an all-time high following the COVID-19 pandemic, as businesses struggled to keep up with rebounding consumer demand. Although labour market tightness, measured by the vacancy-to-unemployment ratio, has largely returned to its pre-pandemic levels, hiring difficulties persist in high-skill sectors and where job quality is low. This poses a risk to long-term economic development, as shortages of skilled labour can hinder productivity growth.

Policy responses to skill shortages require timely and accurate information on skill needs. In response, a growing number of countries have established national skill assessment and anticipation systems. These systems play a crucial role in identifying emerging skill needs, informing education and training policies, and supporting better alignment between labour supply and labour market needs. However, they differ widely in terms of aims, methodology, data and time horizons, which severely limits cross-country comparability.

The *OECD Skills for Jobs Database* provides a harmonised, internationally comparable measure of occupational and skill imbalances for 38 countries. A harmonised approach offers several advantages. It enables the identification of both shared and country-specific shortages and provides a consistent basis for cross-country comparisons. By highlighting differences in imbalances between countries, it also supports policy co-ordination in labour mobility and talent development. In addition, it facilitates learning from other countries' experiences in tackling similar challenges, helping to diffuse effective policy practices.

Occupational imbalances and skill shortages are measured using an objective, data-driven approach. First, a composite indicator of occupational imbalances is constructed from a set of labour market signals, including employment growth, wage growth, growth in hours worked and growth in online job postings (OJP). This indicator ranks occupations according to the extent to which they are in shortage relative to other occupations within each country, with shortage occupations facing relatively greater recruitment difficulties. Second, occupational imbalances are translated into skill shortages, providing policymakers with granular insights into skill needs.

To date, the OECD has released two editions of the Skills for Jobs Database, first in 2017 and then in 2022, with data available up to 2019. The 2026 edition expands the database to include data up to 2024 for most countries and analyses how skill needs have evolved following recent disruptions, including the COVID-19 pandemic and the rapid acceleration in artificial intelligence (AI) adoption. Both have had significant effects on labour demand, with the pandemic driving sectoral reallocation and AI reshaping skill needs within occupations.

The *OECD Skills for Jobs Database 2026* reveals a clear pattern across OECD Member countries: shortages tend to be concentrated in high-skilled occupations, while surpluses are more common in lower-skilled ones. The largest and most persistent shortages are observed among information and communications technology (ICT) professionals, health professionals and teaching professionals.

Shortages of ICT professionals are likely linked to the digital transformation of economies and the rapid development of AI technologies. In many countries, labour supply has struggled to keep pace with this growing demand, resulting in persistent shortages. In the United States, an early leader in the development

and adoption of generative AI, shortages of ICT professionals have intensified since the launch of ChatGPT in 2022. This suggests that demand for ICT professionals is likely to remain strong, particularly in occupations requiring advanced technical expertise and experience. Reducing these shortages will require broadening the supply of ICT talent through career guidance, skills-first hiring practices, flexible learning pathways and micro-credentials, as well as increasing participation among under-represented groups. As ICT skills are increasingly linked to AI development and maintenance, the design of relevant education and training courses will also be crucial.

Health professionals and health associate professionals have been in persistent shortage in OECD Member countries over the last two decades, reflecting a structural imbalance as labour supply has not kept pace with rising demand for healthcare services associated with population ageing and increasing care needs. Reducing these shortages requires educating more health professionals and health associate professionals, as well as expanding entry pathways into healthcare occupations, including for workers transitioning from other sectors. To ensure that education and training provision aligns with evolving labour market needs, these policies should be informed by robust skills anticipation insights. Retention challenges linked to demanding working conditions have further exacerbated the shortages of healthcare workers, underscoring the importance of improving working conditions to attract and retain health workers.

Teaching professionals are also in shortage in OECD Member countries, raising concerns about the quality and sustainability of education systems. While demographic trends are expected to reduce the school-age population in many OECD Member countries, potentially easing demand for teachers in initial education, the growing need for lifelong learning, including upskilling and reskilling opportunities, is likely to maintain or increase the demand for teaching professionals over the longer term. Policies to expand the teaching workforce, including flexible entry pathways and support for second-career teachers, could help tackle these shortages.

While shortages are concentrated in high-skilled occupations, surpluses are more common in lower-skilled and routine occupations. The largest surpluses are observed among clerical support workers, food preparation assistants, labourers, and street and related sales and service workers. For some occupations, particularly clerical occupations, these surpluses may reflect declining demand for administrative and repetitive tasks that are increasingly exposed to automation and AI. Reducing these imbalances will require supporting workers' transitions into occupations in demand through upskilling and reskilling.

Analysis of knowledge, ability and skill shortages broadly reflects the patterns observed across occupations. Knowledge shortages are concentrated in areas associated with in-shortage high-skilled occupations, such as knowledge of computers and electronics and medicine and dentistry. Similarly, shortages in abilities are prevalent for cognitive abilities, which are associated with high-skilled occupations, while physical abilities, which are associated with lower-skilled occupations, are more likely to be in balance. In contrast, transversal skills are generally in shortage, while technical skills, only needed at a high level for very few occupations, are generally in balance. These findings underline the importance of lifelong learning systems that support continuous upskilling and reskilling as skill needs evolve.

More detailed results and the underlying data are available through the *OECD Skills for Jobs Dashboard*: www.oecd.org/en/data/dashboards/skills-for-jobs.html.

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1 Introduction

Persistent skill imbalances are a key challenge for OECD labour markets, with important implications for productivity, innovation and inclusive growth. This chapter examines the causes and consequences of labour and skill imbalances, highlighting the impact of current structural changes on the labour market. It defines key concepts underlying the *OECD Skills for Jobs Database*, including skill shortages, surpluses, mismatches and gaps, and discusses how labour market imbalances can be measured.

Although labour shortages have eased since their peak in 2022, labour market tightness remains above levels observed during most of the pre-pandemic decade (OECD, 2026^[1]). The persistence of shortages despite improving labour market conditions points to structural factors affecting labour supply and demand, rather than cyclical pressures.

Population ageing is one such factor. In regions with the highest old-age dependency ratios, shrinking workforces could increase labour shortages by around 15% over the next 15 years (OECD, 2026^[1]). At the same time, shortages are not only a question of the number of available workers, but also whether workers have the skills that employers need. Digitalisation, the diffusion of artificial intelligence (AI) and the transition to a low-carbon economy are changing skill requirements for many occupations (OECD, 2023^[2]; OECD, 2024^[3]; OECD, 2024^[4]; Cedefop and UNESCO-UNEVOC, 2025^[5]; OECD, 2025^[6]). These changes may contribute to growing skill mismatches if workers do not acquire the new skills demanded by employers. Existing evidence suggests that such mismatches are already widespread. According to the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills 2023, around 9% of workers report being underqualified for their job, while 10% report being under-skilled (OECD, 2024^[4]).

Labour shortages are also not limited to highly skilled occupations. Many occupations requiring medium-level, occupation-specific skills, particularly in construction, transport and personal services, continue to face persistent recruitment difficulties (European Labour Authority, 2026^[7]). In some cases, these shortages may reflect lower job quality rather than a lack of available workers, as demanding working conditions, non-standard hours and limited flexibility can make these occupations less attractive. The COVID-19 pandemic further accelerated a shift in worker preferences towards greater flexibility and work-life balance, making it even harder to attract workers to some occupations (Causa et al., 2022^[8]; Causa et al., 2025^[9]; Knez and Arpaia, 2026^[10]).

As labour and skill shortages increasingly reflect structural rather than cyclical factors, developing policies to reduce them has become a policy priority. Effective responses depend on identifying these imbalances and determining whether they stem from demographic change, skill mismatches, labour market frictions or job quality challenges. The following section reviews the main drivers of labour and skill imbalances and discusses their implications for workers, firms and economic performance.

1.1. Causes and consequences of skill imbalances

In standard textbook models of the labour market, imbalances between labour demand and labour supply are resolved through wage adjustments and worker mobility (Brave et al., 2026^[11]). When labour demand exceeds labour supply, firms raise wages to attract additional workers. Conversely, when labour supply exceeds labour demand, competitive pressures compel job seekers to accept lower wages and induce firms to increase hiring, thereby restoring equilibrium.

In practice, quick adjustment is prevented by various labour market frictions. For example, imperfect information leads students and workers to form biased expectations about future skill demand, while firms cannot fully observe worker productivity prior to hiring (Spence, 1978^[12]; Mortensen and Pissarides, 1994^[13]; Wiswall and Zafar, 2015^[14]). At the same time, mobility and reskilling are constrained by education, training and job-search costs (Becker, 1964^[15]; Pissarides, 2000^[16]; Lochner and Monge-Naranjo, 2012^[17]; Lochner and Monge-Naranjo, 2016^[18]). In addition, geographical mobility is constrained by housing affordability, which can prevent workers from relocating to areas where labour demand is strongest (Cavalleri, Luu and Causa, 2021^[19]). Wage adjustment is further slowed by wage rigidities, as wages do not easily fall or rise in response to changing labour market conditions (Shapiro and Stiglitz, 1984^[20]; Akerlof and Yellen, 1990^[21]).

In addition to these frictions, structural forces affect both the level and the composition of the workforce. By 2060, the working-age population is projected to decline by around 8% on average in the OECD, and by more than 30% in a quarter of the Member countries, putting downward pressure on labour supply (OECD, 2025^[6]). At the same time, digitalisation, the rise of AI and decarbonisation are reshaping the demand for skills across occupations (OECD, 2023^[2]; OECD, 2024^[3]; OECD, 2024^[4]; Cedefop and UNESCO-UNEVOC., 2025^[5]; OECD, 2025^[6]). This combination of declining labour supply and shifting skill demand further increases the risk of labour and skill shortages.

Skill shortages have significant implications at the individual, firm and national levels. At the individual level, skill mismatches are associated with lower wages and job satisfaction, as well as reduced employment prospects (Wolbers, 2003^[22]; Bédoué and Giret, 2011^[23]; Quintini, 2011^[24]; Badillo-Amador and Vila, 2013^[25]; Montt, 2015^[26]; Kim and Choi, 2018^[27]). At the national level, skill shortages undermine competitiveness and constrain economic growth, especially when concentrated in innovation-intensive sectors such as information technology and healthcare (Mavromaras, McGuinness and Wooden, 2007^[28]; McGowan and Andrews, 2017^[29]).

At the firm level, skill gaps and shortages depress productivity, hinder innovation and profitability and raise employee turnover (Tang and Wang, 2005^[30]; OECD, 2012^[31]; Maynard and Parfyonova, 2013^[32]; Brunello and Wruuck, 2021^[33]; Fanti, Guarascio and Tubiana, 2021^[34]; Horbach and Rammer, 2022^[35]). However, the effects are not uniform. Young and small firms are more likely to report recruitment difficulties (European Commission, 2023^[36]; Filippucci, Laengle and Marcolin, 2025^[37]), which may partly reflect lower wages and job quality compared to larger, more established firms (Brown and Medoff, 1989^[38]; Berlingieri, Calligaris and Criscuolo, 2018^[39]; Calvino et al., 2025^[40]). The pattern is similar across the productivity distribution: in low-productivity firms, shortages are often linked to wage and working condition constraints, whereas in high-productivity firms they more often reflect a scarcity of specialised skills (Bergeaud, Cetté and Stary, 2022^[41]; Camussi et al., 2025^[42]; Filippucci, Laengle and Marcolin, 2025^[37]).

In some cases, shortages can also trigger positive responses, prompting investment in physical capital through automation or in human capital through training (Acemoglu, 2010^[43]; Danzer, Feuerbaum and Gaessler, 2024^[44]; Dueholm, Kalyani and Ozkan, 2024^[45]; OECD, 2024^[46]; Ugurlu and Aboobaker, 2025^[47]). However, the recent period of intense labour shortages did not have a significant impact on investment, which remains below the pre-pandemic levels in many economies (OECD, 2025^[48]).

1.2. Definitions and measures of skill imbalances

Skill imbalances are generally defined as imbalances between the supply of and demand for workers, or specific skills, at given wages and working conditions (Veneri, 1999^[49]; Barnow, Trutko and Schede Piatak, 2013^[50]; Eurofound, 2024^[51]; Filippucci, Laengle and Marcolin, 2025^[37]). Surpluses occur when labour supply exceeds labour demand, while shortages arise when demand exceeds supply. Furthermore, shortages may lead to skill mismatches, as employers unable to find the required skills may have to settle for underqualified candidates (OECD, 2017^[52]; Brunello and Wruuck, 2021^[33]; Filippucci, Laengle and Marcolin, 2025^[37]). Such mismatches can persist even when aggregate labour supply and demand appear broadly balanced.

Measuring skill imbalances remains a major conceptual and empirical challenge, as skills are not directly observable and must therefore be proxied (see Box 1.1). Traditionally, this has been done using unidimensional measures such as occupation or educational attainment, reflecting both the state of economic theory and data availability. More recently, the literature has moved towards multidimensional measures of skills, distinguishing between cognitive, personality and social skills – for a review, see Woessmann (2025^[53]).

Box 1.1. The evolution of the concept of skills in economics

Skills were brought to the forefront of economic analysis by human capital theory, which posits that investments in education and training help people acquire skills and knowledge that increase productivity and earnings (Schultz, 1961^[54]; Becker, 1964^[15]). However, in the absence of direct measures, skills were typically proxied by educational attainment (Mincer, 1974^[55]; Griliches, 1977^[56]; Card, 1999^[57]; Heckman, Lochner and Todd, 2006^[58]).

In the 1990s, the concept of skill-biased technological change was used to explain the increasing demand for more skilled workers, with wages reflecting their relative scarcity when the expansion of education lags behind (Tinbergen, 1974^[59]; Katz and Murphy, 1992^[60]; Goldin and Katz, 2018^[61]). Despite this stronger emphasis on skills, empirical analyses continued to rely primarily on educational attainment or occupations as a proxy for skills (Katz and Murphy, 1992^[60]; Berman, Bound and Griliches, 1994^[62]; Autor, 2020^[63]).

In the 2000s, employment growth was observed at both the high- and lower-skilled ends of the occupational distribution, while middle-skilled jobs declined (Autor, Katz and Kearney, 2006^[64]; Goos and Manning, 2007^[65]). This job polarisation has been linked to the routinisation hypothesis, which posits that technological change does not affect broad groups of high- and lower-skilled workers uniformly (Autor, Levy and Murnane, 2003^[66]). Rather, it operates at the level of tasks, substituting for routine activities while complementing non-routine ones. An important conceptual refinement in this literature is the distinction between skills and tasks, where tasks refer to units of work activity, while skills refer to workers' capabilities to perform them (Autor, Levy and Murnane, 2003^[66]; Acemoglu and Autor, 2011^[67]). Empirically, however, task measures are typically constructed at the occupational level, implicitly treating occupations as bundles of similar tasks.

More recently, existing models of education and technology failed to explain why the demand for college-educated labour continued to increase even as the return to cognitive skills declined after 2000 (Castex and Kogan Dechter, 2014^[68]; Edin et al., 2022^[69]). This prompted a shift towards multidimensional conceptions of human capital, recognising that labour market outcomes depend on combinations of cognitive and social skills rather than a single skill dimension (Deming, 2017^[70]; Deming, 2023^[71]).

Unidimensional proxies (occupations and educational attainment) of skills have several advantages. People acquire skills through formal education and workplace training that are often oriented toward particular occupations, while firms use occupational categories to communicate job requirements and evaluate potential applicants (Levenson and Zoghi, 2007^[72]). Moreover, occupational classifications are widely used in statistical systems and administrative records, providing researchers with a standardised and readily observable measure that is available across datasets, countries and time periods.

However, unidimensional proxies are not unproblematic (Levenson and Zoghi, 2007^[72]; Labussi re and Bol, 2026^[73]). A growing body of literature questions the assumption of occupations as bundles of skills. First, skill requirements differ widely within occupations (Yamaguchi, 2012^[74]; Labussi re and Bol, 2026^[73]). For example, building a house requires more complex skills than installing a bookshelf, although both people doing the work could be classified as carpenters. This within-occupation skill variation persists even when using detailed occupational categories (Autor and Handel, 2013^[75]; Cassidy, 2017^[76]; Freeman, Ganguli and Handel, 2020^[77]; Martin-Caughey, 2021^[78]). Second, workers transfer skills from one occupation to another, which implies that skills overlap across different occupations (Poletaev and Robinson, 2008^[79]; Gathmann and Sch nberg, 2010^[80]; Cheng and Park, 2020^[81]).

Educational attainment faces similar limitations as a proxy for skills. First, individuals with the same level of education can possess very different skill levels. This is because educational qualifications do not capture differences in the quality of education and the skills actually acquired through schooling (Hanushek and Woessmann, 2008^[82]; Woessmann, 2025^[53]). In addition, skills are developed not only through formal education but also through workplace experience, training and other forms of non-formal learning that are not reflected in educational qualifications (Heisig and Solga, 2017^[83]).

In response to these limitations, a growing literature measures skills directly rather than relying on occupations or educational attainment as proxies. This work conceptualises skills as multidimensional: basic skills, such as cognitive, personality and social skills, are used to acquire applied skills, which in turn are used to perform work tasks (Woessmann, 2025^[53]). The expansion of this research stream has been facilitated by the increasing availability of large-scale data sources, including job postings and online professional profiles, which offer detailed information on skill needs and workers' skill portfolios.

While multidimensional measures provide a more detailed representation of skills, they also require researchers to make choices about which skills to measure and how to measure them, which can affect empirical findings. For example, cognitive skills are better captured by extensive domain-specific assessments, such as the PIAAC Survey of Adult Skills, than by brief IQ tests, which may miss skills that develop over the life course (Hanushek et al., 2015^[84]). Thus, although multidimensional measures address some limitations of occupational and educational proxies, they do not eliminate measurement issues but relocate them to the skill level.

Given these measurement challenges, the approach for the Skills for Jobs Indicator combines the advantages of occupational classifications with detailed information on skill requirements. Rather than treating occupations as skills, we use occupations as containers of skill requirements and link them to O*NET data on the skills, knowledge and abilities associated with each occupation. This approach retains the comparability and broad availability of occupational data while allowing for a more nuanced characterisation of the skills associated with different jobs. Given the diversity of definitions used in the literature, Box 1.2 summarises the key concepts and terminology used throughout this report.

Box 1.2. Terminology

Jobs

A job is a set of tasks performed by a particular worker in the expectation of economic remuneration (Hauser and Warren, 1997^[85]).

Occupations

An occupation is a category used to group and classify similar jobs (Hauser and Warren, 1997^[85]). There are different ways of classifying occupations into comparable categories, the most common one being the International Standard Classification of Occupations (ISCO), which has been developed by the International Labour Organization (ILO, 2012^[86]).

Skills

Skills are broadly defined as knowledge, skills, abilities and competences, and, where relevant, education (OECD, 2017^[52]). Following O*NET's definition, knowledge refers to organised sets of factual and procedural information within specific domains; skills are developed capacities that facilitate learning and the performance of tasks across occupations; and abilities are enduring individual attributes that influence performance (Boese et al., 2001^[87]).

Imbalances

Skill shortages occur when employers are unable to recruit workers with the required skills at prevailing wages and working conditions in a specific location and time (Veneri, 1999^[49]; Barnow, Trutko and Schede Piatak, 2013^[50]; Eurofound, 2024^[51]; Filippucci, Laengle and Marcolin, 2025^[37]). They can be described as an inadequate supply of workers in high-demand occupations or of the skills needed to perform tasks associated with those occupations.

Skill surpluses occur when the supply of a skill exceeds demand, typically during periods of high unemployment or as a result of a misalignment between education choices and labour market demand (OECD, 2017^[52]).

Skill mismatches arise when workers' skills do not align with employers' requirements. They can persist even in otherwise balanced labour markets and are typically measured as discrepancies between workers' educational attainment or field of study and job requirements, as well as through self-reported assessments of whether workers' skills match job requirements.

Skill gaps occur when employees lack the skills required for their current job, according to their employers (OECD, 2024^[46]). Unlike skill shortages, which relate to recruitment difficulties, skill gaps are identified at the firm level and concern the skills of existing employees.

2 Methodological considerations

Measuring occupational shortages is challenging as no single indicator captures the imbalance between labour demand and supply. The existing literature has generally taken one of two approaches: subjective or objective measures. The OECD Skills for Jobs Indicator takes the latter approach, creating a composite indicator for occupational imbalances and translating it to skill shortages using O*NET job profiles. The composite indicator consists of six labour market signals, including wage growth, growth in hours worked, the unemployment rate, change in underqualification, employment growth and growth in online job postings. This chapter explains the choice of these six labour market signals and presents the data and methodology used to compute the Skills for Jobs Indicator.

2.1. Indicators of occupational imbalances

Measuring occupational imbalances is challenging, as no single metric fully captures the imbalance between labour demand and supply for occupations or skills. The literature commonly distinguishes between two broad approaches, subjective approaches or objective approaches, outlined in Box 2.1 (OECD, 2017^[52]; McGuinness et al., 2025^[88]). The Skills for Jobs Indicator builds on the objective approach developed in OECD (2017^[52]) and OECD (2022^[89]), which provides a harmonised framework for analysing occupational imbalances across OECD Member and partner countries.

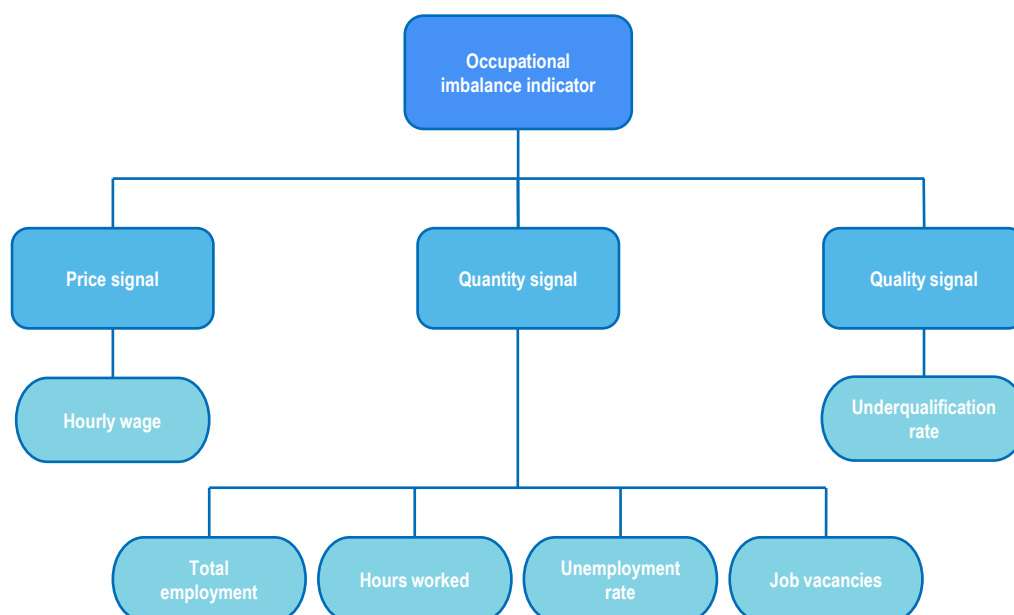
Box 2.1. Approaches to measuring imbalances

Traditionally, imbalances were measured using subjective approaches, such as employer surveys or expert interviews (Filippucci, Laengle and Marcolin, 2025^[37]; OECD, 2026^[90]). These can provide early signals of labour market tightness, but their results are often inconsistent. For example, Greek employers report among the highest labour shortages in the Manpower survey and yet they are among the lowest in the Employer Business Indicators survey (European Commission, 2015^[91]). Such inconsistencies reflect the subjective nature of self-reported data (Green, Machin and Wilkinson, 1998^[92]). Employers may also conflate genuine labour shortages with firm-specific recruitment difficulties caused by low wages or poor working conditions (Barnow, Trutko and Schede Piatak, 2013^[50]; Green et al., 2020^[93]). In some cases, employers may strategically overstate labour scarcity to prompt government intervention, thereby securing supply of the skills they require at wage levels below those that would prevail under undistorted market conditions (Downs, 2009^[94]; Hogarth, 2016^[95]).

Given these shortcomings, objective approaches have gained increasing prominence in national and international assessments of labour shortages and skill needs (Downs, 2009^[94]; OECD, 2017^[52]; OECD, 2022^[89]; Cedefop, 2024^[96]; McGuinness et al., 2025^[88]; OECD, 2026^[90]). These approaches rely on administrative and statistical labour market data rather than employer perceptions and aim to provide a more consistent and comparable basis for identifying occupational and skill imbalances. A key limitation of the objective approach is that changes in these indicators may also reflect factors unrelated to shortages, such as business cycle fluctuations, labour market regulations or external shocks such as COVID-19 (OECD, 2017^[52]; McGuinness et al., 2025^[88]). Combining multiple indicators helps mitigate these limitations, but results may still vary depending on the methodology.

The approach draws on six signals of shortages, including price measures (wage growth), quantity measures (employment growth, unemployment rates, growth in online job postings [OJP] and growth in hours worked) and quality measures (the underqualification rate). As none of these indicators provides a direct measure of shortages, they are combined into a composite index to identify occupational imbalances (see Figure 2.1). To better understand how these measures capture labour market imbalances, the following section examines each indicator in turn, highlighting both their strengths and their limitations as proxies for occupational shortages.

Figure 2.1. Labour market signals underlying the Skills for Jobs Indicator



Source: Author's adaption based on OECD (2017^[52]), *Getting Skills Right: Skills for Jobs Indicators*, <https://doi.org/10.1787/9789264277878-en>.

2.1.1. Wages

The textbook response to labour or skill shortages are wage increases. When labour demand exceeds supply, upward wage pressure should help restore equilibrium. Empirical research supports this claim: employers tend to raise wages when faced with increased competition for workers (Terry and De Zeeuw, 2018^[97]; Le Barbanchon, Ronchi and Sauvagnat, 2023^[98]; Groiss and Sondermann, 2025^[99]; Zwysen, 2026^[100]). As employers typically rely first on less costly and more flexible responses, such as reorganising work, increasing hours, or investing in training, wage increases signal more pronounced or persistent shortages (Healy, Mavromaras and Sloane, 2015^[101]).

However, institutional factors can weaken the link between wages and labour market conditions. In some sectors, particularly the public sector, wage-setting rules limit the scope to offer competitive wages for high-demand occupations or senior positions (Katz and Krueger, 1993^[102]; International Bank for Reconstruction and Development / The World Bank, 2021^[103]; Marcinkowski, Butnaru and Rabrenović, 2024^[104]). Collective bargaining can also compress wage responsiveness, as wages adjust following re-negotiation of collective agreements rather than current labour shortages (Kölling, 2022^[105]; Adamopoulou, Díez-Catalán and Villanueva, 2025^[106]). Adjustments to the minimum wage may also lead to wage growth that is unrelated to skill shortages, particularly in lower-skilled occupations.

Compositional effects may further cloud the interpretation of wage developments. Changes in the workforce structure – such as the retirement of senior, higher-paid workers, or the entry of younger cohorts – can affect average wage growth independently of underlying wage pressure (OECD, 2017^[52]).

2.1.2. Employment

Employment growth within an occupation indicates rising demand for workers with a given skill set and when demand persistently exceeds supply, shortages may emerge. Yet, employment growth is an imperfect indicator of labour shortages, as rising employment may also indicate that firms can fill vacancies without major difficulties. For example, during periods of economic recovery, rapid employment growth often reflects the re-absorption of previously unemployed or underemployed workers rather than labour scarcity. Moreover, when employers perceive shortages to be temporary, they may opt for other measures instead of expanding employment. Such adjustments may include increasing hours worked, reallocating tasks within firms or raising wages to retain existing staff (Mathä et al., 2021^[107]). Finally, employment growth is also shaped by cross-country differences in employment protection legislation, which can slow firms from adjusting employment when facing shortages (Martin and Scarpetta, 2012^[108]). In countries with strict hiring and firing rules, employment changes may be a less reliable signal of labour imbalances.

2.1.3. Unemployment rate

A low unemployment rate for a specific occupation may indicate a shortage, as few qualified candidates are available. In contrast, a high unemployment rate may indicate a surplus. A key limitation is that occupation-specific unemployment measures implicitly assume that jobseekers are tied to their previous occupation. In practice, however, workers may switch occupations in response to changes in wages, working conditions or preferences (Causa et al., 2022^[8]; Liu-Lastres, Huang and Bao, 2023^[109]). In addition, such measures do not capture recent graduates who are available to fill vacancies but lack labour market experience. Moreover, even when the unemployment rate for an occupation is low overall, available workers may be located in regions different from where the jobs are. Finally, a low unemployment rate may mask a surplus if workers are employed but working fewer hours than they would like (Hashimoto, Ono and Schlegl, 2023^[110]).

2.1.4. Hours worked

Increases in hours worked can serve as an early signal that firms are struggling to fill vacancies, as work intensity can typically be adjusted more rapidly than employment levels (Hamermesh, 1986^[111]; Hart, 2023^[112]). Firms tend to increase working hours for current employees when they face short-term demand fluctuations or slow recruitment processes (Healy, Mavromaras and Sloane, 2015^[101]). However, relying on higher work intensity is generally not a viable long-term response to labour shortages, as overtime work can increase turnover, potentially worsening staffing shortages faced by firms (Tan et al., 2020^[113]; Bae, 2024^[114]). Furthermore, some occupations do not allow deviation from prescribed schedules, limiting adjustments through working hours (Hart, 2023^[112]).

2.1.5. Vacancies

Hiring often begins with the posting of a vacancy to attract job seekers (Davis, Faberman and Haltiwanger, 2013^[115]). Job vacancies are therefore widely used as a proxy for labour demand (Downs, 2009^[94]; Causa et al., 2022^[8]; Domash and Summers, 2022^[116]; Barnichon and Shapiro, 2024^[117]; Causa et al., 2025^[9]). High vacancies (labour demand) relative to unemployment (labour supply) may indicate that employers struggle to find suitable workers.

However, job vacancies capture only a subset of overall hiring demand, as many positions are filled through informal channels such as employee referrals or internal recruitment (Ioannides and Loury, 2004^[118]; Davis, Faberman and Haltiwanger, 2013^[115]). These channels are often preferred by firms because they reduce search costs and increase the likelihood of successful and durable matches (van Ours, 1989^[119]; Burks et al., 2015^[120]; Gürtzgen and Pohlman, 2024^[121]). Vacancy-based measures should therefore be interpreted as partial indicators of labour demand.

Beyond these conceptual limitations, commonly used vacancy-based indicators, such as vacancy rates, do not capture how long positions remain unfilled. If vacancies are filled quickly, high vacancy rates may simply reflect normal labour market dynamics rather than genuine shortages. Second, vacancy levels vary substantially across occupations (Barnow, Trutko and Piatak, 2013^[122]). Occupations with low pay and limited career prospects, such as those in the hospitality sector, tend to have higher turnover rates and therefore more vacancies (Downs, 2009^[94]; McGinley et al., 2014^[123]; Dogru et al., 2023^[124]). In contrast, there may be fewer civil service openings, as public-sector workers tend to stay in their job for long periods (Fontaine et al., 2020^[125]). Finally, hiring difficulties may reflect poor working conditions, low pay, or ineffective human resource practices rather than genuine labour shortages (OECD, 2017^[52]).

Using vacancy data as an indicator of labour demand also requires careful methodological consideration. Official vacancy statistics are typically produced either by national statistical offices, based on representative employer surveys of positions firms intend to fill in the near future, or by public employment services, based on vacancies reported by employers for job-matching purposes (Hershbein and Kahn, 2018^[126]). However, vacancy data from public employment services may not be fully representative of overall labour demand, as reporting is typically voluntary and recruitment often takes place through alternative channels. This can lead to systematic biases in coverage, with high-skilled occupations typically underrepresented (Zilian, Zilian and Jäger, 2021^[127]). Cross-country comparisons are further complicated by differences in vacancy definitions and measurement practices (Napierala, Kvetan and Branka, 2022^[128]).

OJP are a complement to official job vacancy statistics, providing timely and detailed information on labour demand (Sostero and Fernández-Macías, 2021^[129]; Fabo and Kurekova, 2022^[130]). Conceptually, OJP capture only a subset of all vacancies – namely, those that are publicly advertised on online platforms. Moreover, the decision to advertise a vacancy online is not random, which introduces additional selection bias in OJP data. OJP tend to overrepresent high-skilled jobs and underrepresent lower-skilled jobs, public sector jobs and jobs in small businesses (Hershbein and Kahn, 2018^[126]; Cammeraat and Squicciarini, 2021^[131]; Sostero and Fernández-Macías, 2021^[129]; Tsvetkova et al., 2024^[132]). However, this may be less of a problem when there are labour shortages, as firms are then forced to broaden their search through formal vacancy postings (Moreno Galbis, Wolff and Herault, 2020^[133]; Fabo and Kurekova, 2022^[130]).

Another concern is that the declining cost of online recruitment enables firms to post more ads or keep them open longer, increasing observed vacancy counts independently of labour demand (Causa et al., 2025^[9]). Comparisons between OJP and official vacancy statistics reveal substantial discrepancies across countries, with some datasets reporting significantly more vacancies than the official statistics (Tsvetkova et al., 2024^[132]). This discrepancy may partly reflect differences in coverage, definitions and data collection methods. However, it may also arise from postings that employers have no immediate intention of filling, such as to build a candidate pipeline, signal growth to investors, or manage employee expectations (Weber Handwerker and Pepper, 2025^[134]).

2.1.6. Underqualification

When labour demand and supply are misaligned, the quality of matches deteriorates (OECD, 2017^[52]; Brunello and Wruuck, 2021^[33]; Filippucci, Laengle and Marcolin, 2025^[37]). During economic expansions, when the labour market tightens, employers may struggle to find candidates with the desired skills and adjust by hiring workers whose skills do not fully match job requirements (Veneri, 1999^[49]). Conversely, during recessions, when jobs become scarce, skilled workers are more willing to accept positions requiring lower levels of education and fewer skills (Liu, Salvanes and Sørensen, 2016^[135]; Blázquez Cuesta, Pérez Navarro and Sánchez-Mangas, 2025^[136]). As a result, expansions tend to increase underqualification and underskilling, while downturns raise the incidence of overqualification and overskilling. Beyond cyclical dynamics, structural trends – including digitalisation, decarbonisation and population ageing – increase demand for specialised skills that may be scarce in the labour force, thereby heightening the risk of

mismatch (Filippucci, Laengle and Marcolin, 2025^[37]). Therefore, a rise in the underqualification rate may signal labour shortages and is used as a quality-based shortage indicator. Overqualification, by contrast, is more likely to reflect skill underutilisation.

Box 2.2. COVID-19 impact on labour market indicators

The COVID-19 pandemic triggered a large economic contraction, resulting in the loss of 114 million jobs globally by the end of 2020 (OECD, 2021^[137]). As a result, it introduced disruptions that affected the labour market indicators used in this analysis. These effects were highly heterogeneous across countries, sectors and occupations.

In the United States and Canada, labour-market adjustment occurred primarily through layoffs, leading to significant reductions in employment and corresponding increases in unemployment (OECD, 2021^[137]). By contrast, in many European economies that implemented short-time work and job-retention schemes, adjustment took place mainly through reductions in working hours rather than job losses: an estimated 90% of total hours lost were borne by workers who remained employed. Hours fell most sharply in low-paying and contact-intensive sectors, such as hospitality, tourism, arts and leisure. Usual hours worked, which are typically less volatile than actual hours, also decreased in many EU Member States between 2019 and 2022 (Eurofound, 2023^[138]).

Although government policies mitigated the impact on employment, some workers still temporarily withdrew from the labour force due to health risks, care responsibilities, or limited job opportunities (OECD, 2021^[139]; Braakmann, Eberth and Wildman, 2022^[140]). These inactive workers are not captured in the official unemployment statistics.

During the early stages of the COVID-19 pandemic, the high uncertainty and restrictions on movement led to a collapse in job vacancies across all sectors and occupations (Forsythe et al., 2020^[141]; OECD, 2021^[137]). Following economic reopening and fiscal support, vacancies surged sharply before returning to pre-COVID levels by 2025 (Feist, 2024^[142]; OECD, 2025^[6]). Nevertheless, whether vacancy rates provide a clear signal of labour demand during and immediately after the COVID-19 pandemic remains debated (Restrepo-Echavarria and Cheremukhin, 2022^[143]; Horwich and Mongey, 2023^[144]; Causa et al., 2025^[9]).

The pandemic also distorted wage signals, making wages less responsive to underlying labour market tightness. In many countries, governments introduced job-retention schemes under which employers received support covering a significant share of the wages of employees working reduced hours (OECD, 2021^[137]). As a result, nominal wages generally did not adjust downwards during the pandemic, reflecting the well-documented downward rigidity of wages (Braakmann, Eberth and Wildman, 2022^[140]). Consequently, the widespread use of job-retention schemes may have introduced some distortions in wage statistics (OECD, 2024^[145]).

Taken together, these factors suggest that labour market indicators observed during the pandemic and the immediate recovery period should be interpreted with caution. The unprecedented nature of the shock, combined with widespread policy interventions, temporarily weakened the link between standard indicators and underlying labour market imbalances. As a result, signals derived from employment, unemployment, vacancies, hours worked and wages may not reliably reflect the presence or absence of occupational shortages in these years.

2.2. Method behind the Skills for Jobs Indicator

Building on previous editions of the *OECD Skills for Jobs Database*, the Skills for Jobs Indicator is computed in two steps: first, a composite indicator for whether each occupation is in shortage or surplus is computed based on six labour market signals (OECD, 2017^[52]; OECD, 2022^[89]). Second, the occupation shortages are converted to skill shortages using the O*NET skills taxonomy. The methodology is designed to draw on internationally comparable data and use a harmonised method, ensuring consistency in the cross-country measurement of occupational and skill imbalances for 38 countries. It has been modified slightly since the previous edition by including an additional signal, OJP, and adjusting the method used to translate occupation shortages to skill shortages. This section describes the methodology used to construct the Skills for Jobs Indicator.

2.2.1. Step 1: Computing occupational imbalances

The occupational imbalance indicator is a composite indicator that ranks occupations according to the extent to which they are in shortage or surplus within each country. It is based on six signals of labour market pressure: hourly wage growth, growth in hours worked, employment growth, the unemployment rate, the annual change in the underqualification rate and growth in the number of OJP. Since the unemployment rate and labour shortages are negatively related, i.e. low unemployment rate is associated with shortages, the inverse unemployment rate is used in the indicator (definitions of the variables underlying each signal are provided in Box 2.3) Using the inverse unemployment rate allows all labour market signals to enter positively into the Skills for Jobs Indicator. The selection of these signals is grounded in the theoretical and empirical evidence presented in Section 2.1.

The inclusion of OJP growth is a recent refinement of the indicator. From a theoretical perspective, OJP are a good proxy for labour demand and a sharp increase in the number of OJP may signal an increase in labour market pressures. Their use has previously been constrained by limited availability of cross-country comparable data and sufficiently long time series. However, recent advances in data collection and processing have improved the coverage and reliability of OJP data, enabling OJP to be included in the indicator.

Main data sources

To compute the indicator, data on each signal is needed. For all the signals, except for the number of OJP, national labour force surveys compiled by official statistical agencies are predominantly used. These surveys are designed to produce official national statistics on employment and unemployment, ensuring representativeness of the labour force, and often adhere to the same definitions of key indicators, enabling cross-country comparability. Where such data are not available, comparable information is obtained from alternative representative national surveys. Annex Table A.1 provides an overview of the data sources for each country.

Lightcast data is used to compute the number of OJP by occupation. Lightcast data is gathered and formatted by the company Lightcast. They use web scraping algorithms to gather information on OJP, including the occupation, industry and skill requirements, in 165 countries. The coverage of Lightcast data is continuously under development and in recent years they have added numerous new countries, such as Korea. However, this implies that for some countries, the time period is too short to compute the OJP sub-indicator. In such cases, the OJP sub-indicator is excluded (Annex Table A.1 provides an overview of whether the OJP sub-indicator is excluded for each country). For Korea, a national data source was available and used instead.¹ For the majority of countries, Lightcast data is available from 2018, which implies that the vacancy sub-indicator is only included for the most recent years for these countries. This implies that the indicators before and after the inclusion of the vacancy component are not directly comparable.

Box 2.3. Definitions of the signals underlying the occupational imbalance indicator

The six signals of labour market pressure are defined as follows:

- **Hourly wage** is imputed from individuals' gross income from their main job, including all monetary compensation, such as bonuses, overtime pay, etc., divided by the hours usually worked. The median is calculated for each occupation.
- **Hours worked** are based on the hours usually worked by individuals in their primary job. The mean is calculated for each occupation.
- Number of **employed** is the number of people employed in the occupation as their primary job. It follows the ILO's definition of employed, which includes all people within the working age who performed work in the reference period or people who were employed in the reference period but did not work, e.g. because they were on sick leave or maternity leave.
- **Inverse unemployment rate** of each occupation is calculated based on the following formula:

$$\text{Inverse unemployment rate} = 1 - \frac{\text{number of unemployed}}{\text{number of unemployed} + \text{number of employed}}$$

The occupation for the unemployed is based on unemployed people's previous occupation.

- **Underqualification rate** is the share of employed people with their highest attained education level below the modal education level of all employed individuals in the same occupation. The modal education level is calculated at a more granular occupation level to account for differences between occupations within broader occupation groups. The education level is based on the International Standard Classification of Education (ISCED), and the ISCED categories were combined into five categories: primary education or less, lower secondary education, upper-secondary education, post-secondary non-tertiary education and tertiary education.
- Number of **OJP** is the total number of OJP for each occupation.

As with the OJP data, data is not available for all sub-indicators in all countries. This is due to various reasons, e.g. data confidentiality constraints or the absence of sufficiently reliable data sources. In such cases, the affected sub-indicators are excluded from the calculation. However, inclusion in the *OECD Skills for Jobs Database* requires that the wage, employment and usual hours worked sub-indicator can be computed at a minimum. Annex Table A.1 provides an overview of the sub-indicators included in the indicator for each country.

Data breaks

While national surveys, such as labour force surveys, are designed to ensure comparability between waves, methodological changes are sometimes introduced. For instance, during the COVID-19 pandemic, some surveys shifted from in-person to telephone-based data collection. Such changes can result in significant data breaks, complicating the interpretation of trends as observed variations in sub-indicators may reflect both changes in labour market conditions and survey methodology. To mitigate the influence of such discontinuities, each sub-indicator underwent visual inspection for inconsistencies at the occupation-level and breaks were adjusted backwards where necessary. The post-break time series were backward-adjusted using the country-level growth rate in the break year and the growth rates of the pre-break series for earlier years. Annex A provides an overview of the corrected breaks.

Occupation codes

The occupational imbalance indicator is computed at the two-digit ISCO-08 level. ISCO is a classification of occupations managed by the ILO and designed to facilitate international communication on occupations. It classifies occupations from the one-digit level to the four-digit level. For the Skills for Jobs Indicator, there is a trade-off between using a very-detailed ISCO level and ensuring that the sample size underlying each occupation is sufficient to produce robust statistics. To produce detailed information while preserving a sufficient sample size, the two-digit ISCO level was chosen.² If sample sizes at the two-digit level are still insufficient, occupations are merged with closely related occupations (see Annex Table A.1 for an overview of merged occupations by country). For comparability in the report, a common set of merged occupation groups is used for all countries, while the dashboard displays individual occupation indicators whenever these are available.³

Not all countries use the ISCO classification for official statistics but instead rely on national classification systems. For these countries, crosswalks are used to map national occupation codes to ISCO. These mappings are rarely one-to-one, as a single national occupation may correspond to multiple ISCO occupations and vice versa. When one occupation is matched with multiple ISCO occupations, employment counts are apportioned evenly between the corresponding ISCO categories. Employment is then used as a weighting factor in the calculation of the sub-indicators. Lightcast also uses its own occupational taxonomy; however, for most countries, the data are also available using ISCO classification. Where this is not the case, crosswalks are used to convert occupation codes to the ISCO classification.

Computing the composite indicator

Each sub-indicator of the composite indicator is constructed in two steps. First, the underlying trend in each labour market signal is estimated at the occupational level to account for cyclical fluctuations. Second, the trends in the individual signals are compared with economy-wide developments to assess whether labour demand is growing or declining relative to the rest of the economy.

Accounting for cyclical fluctuations is important because the sub-indicators used to capture occupational imbalances respond not only to changes in labour demand and supply, but also to broader macroeconomic dynamics associated with economic expansions and contractions. As a result, changes in the signals may reflect cyclical effects rather than imbalances between the supply of and demand for labour. To alleviate this issue, the underlying trend is separated from cyclical fluctuations by applying the Hodrick-Prescott (HP) filter to each signal. Growth rates for wages, hours worked, number of employed and OJP are based on the trend component extracted using the HP filter. The same is the case for the annual change in the underqualification rate.

The aggregation of the sub-indicators into a composite indicator requires that they are expressed on a common scale. To this end, each sub-indicator is standardised within country and year by subtracting the country-year-mean and dividing by the standard deviation. This implies that the performance of each occupation is evaluated relative to all other occupations within the same country and year.

Given that no single sub-indicator perfectly signals occupational imbalances, they are combined into a composite indicator. The composite indicator is constructed as a weighted average of the sub-indicators, with all sub-indicators entering positively. Equal weights are assigned to all sub-indicators, except for employment and OJP growth, which are assigned half-weights. Employment growth is downweighted because it is an ambiguous indicator, while OJP growth is downweighted because of limitations of OJPs in measuring labour demand (see Section 2.1).

The resulting indicator provides a relative measure of occupational imbalances within each country. Positive values indicate labour shortages, meaning that workers are harder to find than for other occupations, while negative values indicate labour surpluses, meaning that workers are easier to find than for other occupations. Consequently, cross-country differences reflect variation in the relative position of

occupations within national labour markets rather than absolute levels of shortages. Occupations are grouped into five categories ranging from “large surplus” to “large shortage” based on the occupational imbalance indicator.

The occupational imbalance indicator is shaped by the underlying data and methodology. Consequently, its results may differ from country-specific analyses and other indicators that rely on alternative approaches (Skills England, n.d.^[146]; McGuinness et al., 2025^[88]). This is generally the case for objective indicators, as results depend on the methodological choices made. In the context of occupational imbalances, differences may arise from the selection of labour market signals and the aggregation methodology. Furthermore, the Skills for Jobs Indicator captures relative imbalances by assessing the performance of occupations compared with others within the same country and year, while other indicators may measure absolute imbalances by comparing labour supply and demand directly.

2.2.2. Step 2: Translating occupation shortages into skill shortages

To provide an indicator of skill shortages, occupation-level shortages are translated to skill shortages using occupation profiles produced by O*NET. O*NET provides a comprehensive mapping between all occupations and knowledge, abilities and skills for the United States and is widely regarded as one of the most comprehensive and methodologically sound sources on skill use in employment (Beblavy et al., 2016^[147]). Importantly, each occupation-skill pair is assigned a level of the skill required for the occupation and an importance score indicating the significance of the skill for the occupation (see Box 2.4 for more detail), which enables the computation of weights for each pair. Further, the occupation profiles are regularly updated to capture emerging skills and evolving job requirements.

Box 2.4. O*NET occupation profiles and their use for the Skills for Jobs Indicator

The O*NET database provides a detailed and standardised overview of occupation profiles, including detailed information on worker attributes and job characteristics. Developed by the United States Bureau of Labor Statistics, O*NET is designed to capture occupation profiles in the United States’ labour market. Portions of every profile are updated annually using multi-method data collection, including worker surveys and occupational experts. Its breadth, level of detail and relevance have made it a used resource for labour market analysis beyond the United States.

For the Skills for Jobs Indicator a subset of the dimensions included in the occupation profiles are used. These include:

1. **Knowledge**, referring to information and understanding used across different areas of work (e.g. engineering and technology, mathematics or management);
2. **Skills**, capturing developed capacities that facilitate learning and task performance, including both essential skills (e.g. active listening or writing) and transversal skills (e.g. negotiation or programming);
3. **Abilities**, capturing natural talents and capabilities that affect how well someone can perform their work (e.g. originality or manual dexterity).

Each knowledge, skill and ability dimension is assessed in O*NET using two metrics: importance and level. Importance reflects how essential a given dimension is for job performance (measured on a scale from 1 “not important” to 5 “extremely important”) and level captures the degree of proficiency required (measured on a scale from 0 to 6).

Source: www.onetcenter.org/.

While O*NET is designed to reflect occupation profiles in the United States, it has been extensively used for analysis of other countries than the United States (Goos and Manning, 2007^[65]; Aedo and Walker, 2012^[148]). Nevertheless, important caveats apply as differences may exist between occupation profiles in the United States and those in other countries included in the *OECD Skills for Jobs Database*. In particular, O*NET occupation profiles may be less relevant for low-income countries, where technological adoption, institutional frameworks and job design can differ substantially from those in the United States. Potential measurement biases should also be acknowledged. For instance, the composition of the O*NET survey respondents may be skewed towards more highly educated individuals, possibly resulting in upward-biased estimates of skill requirements (Handel, 2016^[149]), although this cannot be directly verified due to limited information on respondents.

The skill shortage indicator builds on the occupational imbalance indicator multiplied by the normalised level and importance of the skill for each occupation. This assigns greater weights to skills that are both highly important and required at a high level. To avoid occupation shortages and surpluses cancelling each other out for the skill indicator and acknowledge that skills may not be readily transferable between occupations, it only focusses on occupations in shortages. This approach implies that only occupations in shortage feed into the measure of skill shortages. When aggregating the results to the skill level, occupation shortages are weighted by their employment shares, ensuring consistency with the relative size of occupations in the labour market.

3

Occupational imbalances, skill shortages and policy implications

This chapter presents results from the *OECD Skills for Jobs Database 2026* for 38 countries. The results reveal persistent shortages concentrated in high-skilled occupations, particularly among information and communications technology professionals, health professionals and teaching professionals, while surpluses are more common in lower-skilled occupations. These imbalances translate into knowledge shortages in areas related to high-skilled occupations, such as computers and electronics and medicine and dentistry knowledge. Cognitive abilities, important for high-skilled occupations, are also in shortage, while physical abilities, important for lower-skilled occupations, are in balance. Among skills, shortages are most often observed in widely used skills, reflecting their importance for many occupations, while specialised technical skills, associated with a narrower set of occupations, often appear in balance. The chapter concludes by presenting key policy recommendations to tackle these imbalances.

3.1. Occupational imbalances

Using the methodology outlined in Section 2.2, occupational imbalances are computed for 38 countries, with the latest available data ranging from 2022 to 2025 depending on the country. Table 3.1, Table 3.2 and Table 3.3 provide an overview of the occupational imbalances for the most recent year available for each country. Orange signifies shortages and blue signifies surpluses, while darker shades indicate larger imbalances. White signifies occupations that are in balance, meaning occupations where the imbalance is negligible. The results can be explored further through the *OECD Skills for Jobs Dashboard*, available at www.oecd.org/en/data/dashboards/skills-for-jobs.html.

On average in the OECD area, shortages tend to be concentrated in high-skilled occupations, whereas surpluses are more common in lower-skilled occupations. Health professionals, teaching professionals and information and communications technology (ICT) professionals face some of the largest shortages, while food preparation assistants and street and related sales and service workers face some of the largest surpluses. There are, however, significant variations between countries. For example, food preparation assistants are in large shortage in Germany, Spain and the United States.

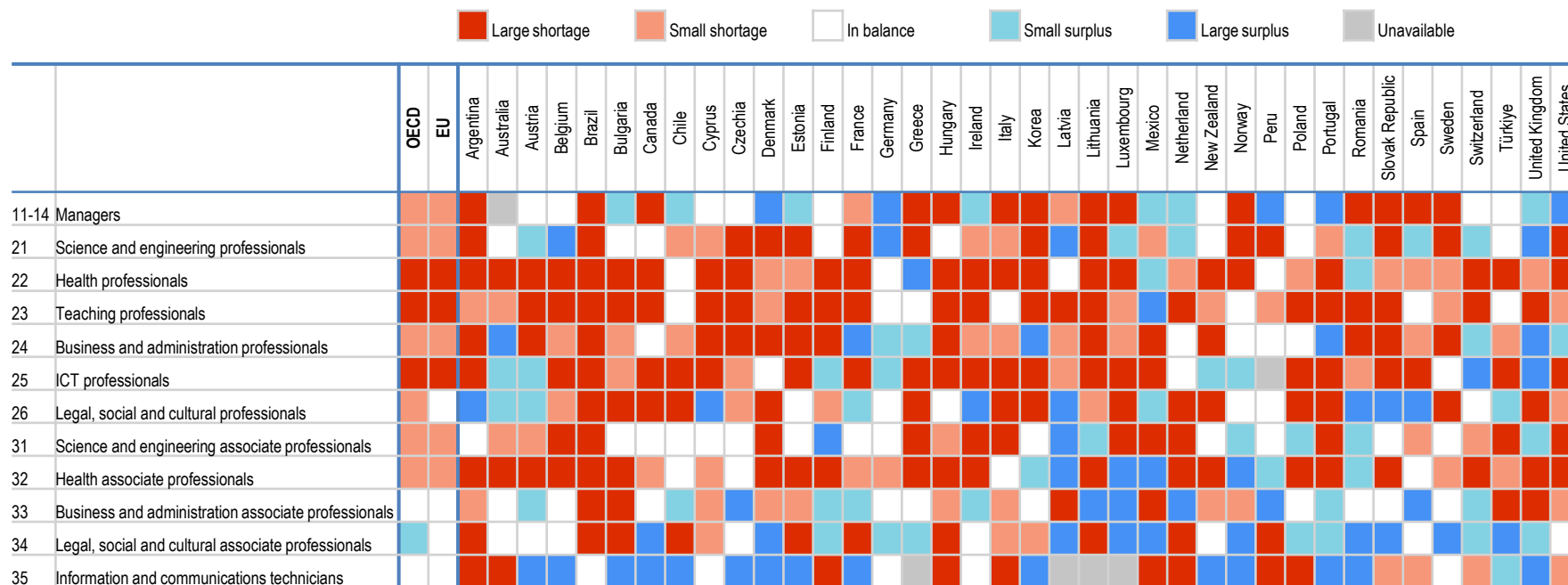
These findings are consistent with the existing literature, which finds that labour shortages are more prevalent in high-skilled sectors (OECD, 2024^[150]; Filippucci, Laengle and Marcolin, 2025^[37]). Labour shortages are also found to be higher in firms with green and digital technologies, which often rely on high-skilled labour. Recent evidence indicates that the adoption of generative AI may disproportionately reduce demand for junior workers, while demand for more experienced workers may remain relatively stable (Hosseini Maasoum and Lichtinger, 2025^[151]; Westby, Modestino and Cheng, 2026^[152]). This points to shortages being concentrated in high-skilled occupations and more senior positions. Supply-side factors may also contribute to labour shortages in high-skilled occupations, where lengthy education and training pathways can limit the responsiveness of labour supply to changes in labour market demand.

Some middle- and lower-skilled occupations are also in shortage, such as metal, machinery and trade workers. This aligns with findings from the European Labour Authority, finding that occupations related to building and construction are facing some of the most severe shortages (European Labour Authority, 2026^[7]). Part of this shortage reflects rising demand in industries related to the green transition. At the same time, retirements are likely to intensify shortages. For example, in EUROpean Employment Service (EURES) countries, workers aged over 50 outnumber those under 30 in these occupations (European Labour Authority, 2026^[7]). The shortages may also be linked to difficulties attracting and retaining workers due to poor job quality, including shift work and exposure to physical and mental health risks (Causa et al., 2025^[9]).

Note that these results may differ from results from national skills assessment exercises and other analyses of labour shortages because of differences in data and methodology. The OECD Skills for Jobs Indicator complements these exercises by providing a harmonised framework that enables consistent comparisons between countries. By offering a comparable measure of occupation and skill imbalances, it can support cross-country learning, inform labour mobility policies and contribute to the co-ordination of policy responses to shared labour market challenges.

Table 3.1. High-skilled occupations are generally in shortage

Occupational imbalances for the most recent year available, by country

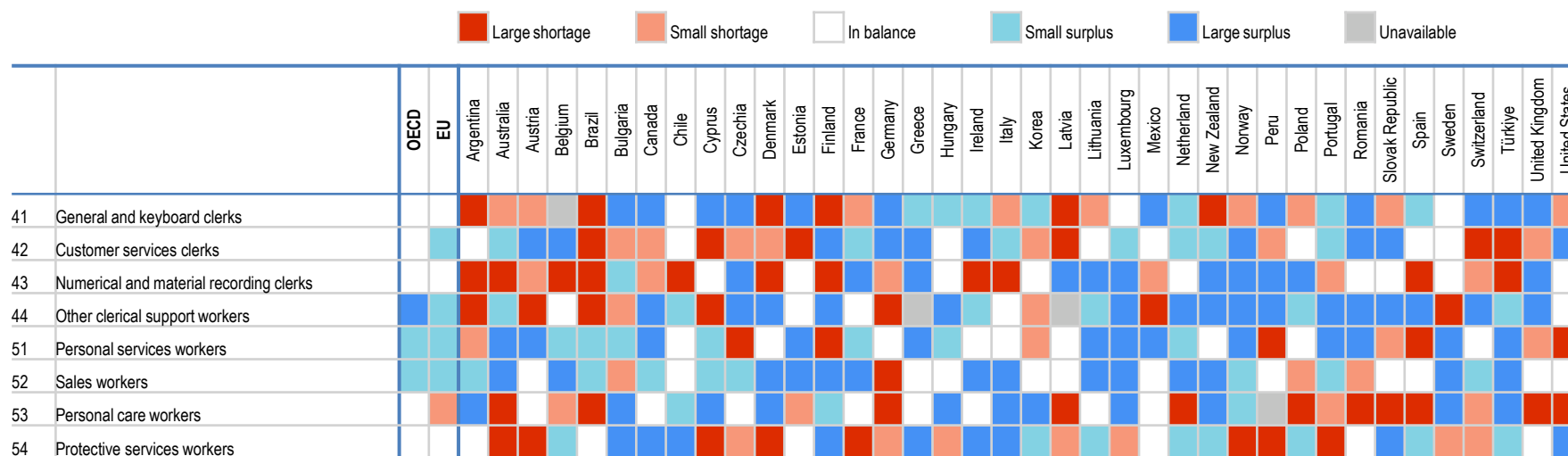


Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the occupation-level indicator in the latest year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table 3.2. Middle-skilled, non-manual occupations are generally in surplus

Occupational imbalances for the most recent year available, by country

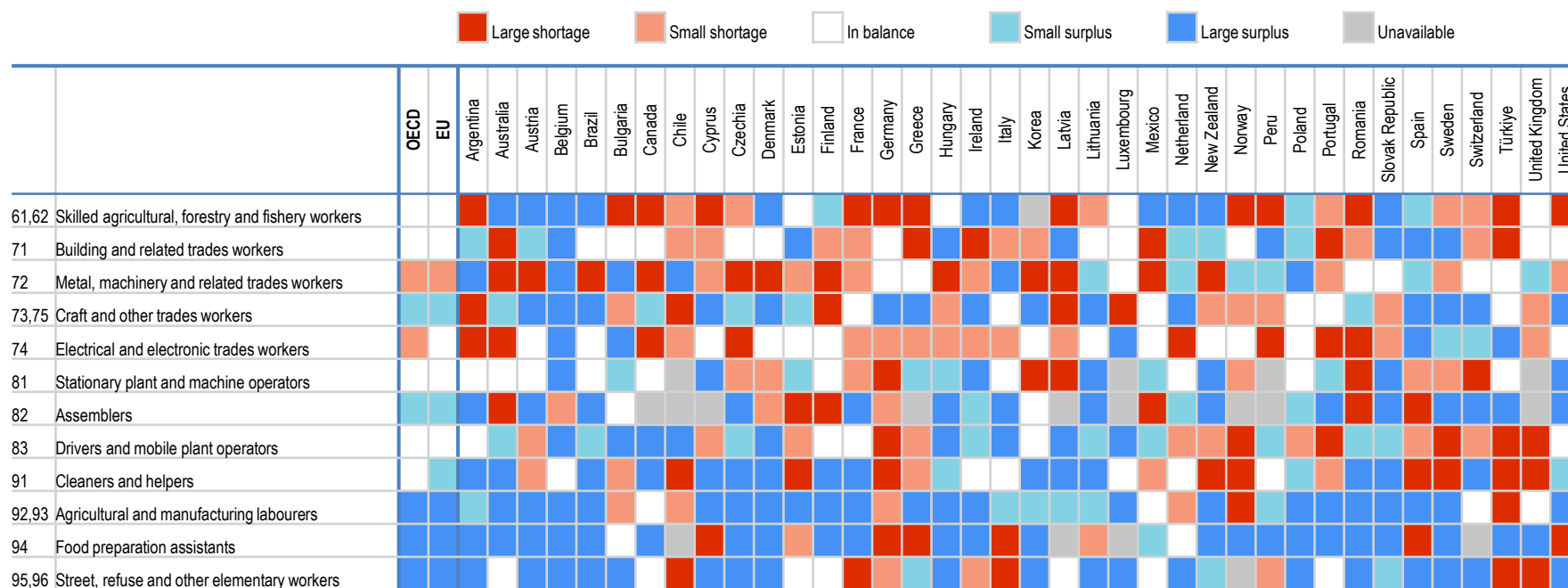


Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the occupation-level indicator in the latest year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table 3.3. Lower-skilled occupations are generally in surplus

Occupational imbalances for the most recent year available, by country



Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the occupation-level indicator in the latest year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

3.1.1. Occupational imbalances over time

As discussed in Section 1, temporary occupational imbalances are not a major concern. Such imbalances are a natural feature of dynamic labour markets, as changes in labour demand are not immediately matched by adjustments in labour supply. However, when these imbalances persist over time, they may signal structural issues and warrant policy attention. To assess the persistence of occupational imbalances, Table 3.4 presents average occupational imbalances for the OECD Member countries from 2019 to 2023 and Table 3.5 to Table 3.8 presents occupational imbalances for a selected set of OECD Member countries, Australia, France, the United Kingdom and the United States.

On average in OECD Member countries, high-skilled occupations are in persistent shortage, while lower-skilled occupations are in persistent surplus. This is similar to the pattern observed for the most recent year available in Table 3.1, Table 3.2 and Table 3.3. Health, teaching and ICT professionals were in shortage from 2019 to 2023, and food preparation assistants were in surplus over the same period. This implies that for high-skilled occupations, labour demand has remained consistently higher than labour supply, while the reverse applies to lower-skilled occupations.

While occupational imbalances are persistent for the OECD area on average, there are significant variations over time at the country-level. For example, while ICT professionals are in shortage for the OECD area on average, Australia experienced a notable reversal, with ICT professionals moving from a large shortage in 2021 to a surplus in 2025. This suggests that in recent years labour demand may have been lower than labour supply or that supply-side measures have increased the number of professionals available to fill job vacancies. Similarly, ICT professionals in the United Kingdom transitioned from being broadly in balance to being in surplus over the same period. In France and the United States, ICT professionals are in persistent shortage, reflecting the rapid expansion of the ICT sector and the inability of supply to keep up.

Health professionals and health associate professionals have on average been in persistent shortage in OECD Member countries, reflecting a structural imbalance as labour supply has not kept pace with rising demand for healthcare services associated with population ageing and increasing care needs (OECD/European Commission, 2024^[154]). Retention challenges linked to demanding working conditions have further exacerbated these shortages (OECD, 2023^[155]; Causa et al., 2025^[9]; OECD, 2025^[156]). The indicator may mask more severe regional imbalances within countries as shortages of healthcare workers are often concentrated in rural regions, which may be less attractive to workers (OECD, 2021^[157]; OECD, 2025^[156]).

Teaching professionals are also in shortage in OECD Member countries, raising concerns about the ability of education systems to meet current and future education needs. At the country-level, Australia, France, the United Kingdom and the United States face persistent shortages of teaching professionals, which may be exacerbated by the ageing population as more teachers are set to retire in the near future (OECD, 2025^[158]). While demographic trends are expected to reduce the size of the school-age population and, consequently, demand for teachers in many OECD Member countries (OECD, 2025^[158]), growing demand for lifelong learning, including upskilling and reskilling opportunities, is likely to sustain or increase demand for teaching professionals over the longer term.

Some occupations have gone from being in surplus or balance in 2019 to being in shortage in recent years. This change is seen for several middle-skilled occupations, such as building, metal and machinery, electrical and electronic and related trades workers in Australia and metal and machinery workers in the United States. This implies that labour supply has not kept pace with rising demand in these occupations.

Table 3.4. Shortages are persistent in the OECD Member countries

Occupational imbalances over time, OECD area average

		2019	2020	2021	2022	2023
		Large shortage Small shortage In balance Large surplus Small surplus				
11-14	Managers					
21	Science and engineering professionals					
22	Health professionals					
23	Teaching professionals					
24	Business and administration professionals					
25	ICT professionals					
26	Legal, social and cultural professionals					
31	Science and engineering associate professionals					
32	Health associate professionals					
33	Business and administration associate professionals					
34	Legal, social and cultural associate professionals					
35	Information and communications technicians					
41	General and keyboard clerks					
42	Customer services clerks					
43	Numerical and material recording clerks					
44	Other clerical support workers					
51	Personal services workers					
52	Sales workers					
53	Personal care workers					
54	Protective services workers					
61,62	Skilled agricultural, forestry and fishery workers					
71	Building and related trades workers (excluding electricians)					
72	Metal, machinery and related trades workers					
73,75	Craft and other trades workers					
74	Electrical and electronic trades workers					
81	Stationary plant and machine operators					
82	Assemblers					
83	Drivers and mobile plant operators					
91	Cleaners and helpers					
92,93	Agricultural and manufacturing labourers					
94	Food preparation assistants					
95,96	Street, refuse and other elementary workers					

Note: The OECD average is the mean of the occupation-level indicator for OECD Member countries included in the Skills for Jobs Database for the given year. The OECD average for 2023 excludes Chile and Norway as the data underlying the indicator is only available for these countries until 2022. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table 3.5. Occupational imbalances in Australia from 2019-2025

		2019	2020	2021	2022	2023	2024	2025
		Large shortage Small shortage In balance Large surplus Small surplus Unavailable						
11-14	Managers							
21	Science and engineering professionals							
22	Health professionals							
23	Teaching professionals							
24	Business and administration professionals							
25	ICT professionals							
26	Legal, social and cultural professionals							
31	Science and engineering associate professionals							
32	Health associate professionals							
33	Business and administration associate professionals							
34	Legal, social and cultural associate professionals							
35	Information and communications technicians							
41	General and keyboard clerks							
42	Customer services clerks							
43	Numerical and material recording clerks							
44	Other clerical support workers							
51	Personal services workers							
52	Sales workers							
53	Personal care workers							
54	Protective services workers							
61,62	Skilled agricultural, forestry and fishery workers							
71	Building and related trades workers (excluding electricians)							
72	Metal, machinery and related trades workers							
73,75	Craft and other trades workers							
74	Electrical and electronic trades workers							
81	Stationary plant and machine operators							
82	Assemblers							
83	Drivers and mobile plant operators							
91	Cleaners and helpers							
92,93	Agricultural and manufacturing labourers							
94	Food preparation assistants							
95,96	Street, refuse and other elementary workers							

Note: The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table 3.6. Occupational imbalances in France from 2019-2024

		2019	2020	2021	2022	2023	2024
		Large shortage Small shortage In balance Large surplus Small surplus Unavailable					
11-14	Managers						
21	Science and engineering professionals						
22	Health professionals						
23	Teaching professionals						
24	Business and administration professionals						
25	ICT professionals						
26	Legal, social and cultural professionals						
31	Science and engineering associate professionals						
32	Health associate professionals						
33	Business and administration associate professionals						
34	Legal, social and cultural associate professionals						
35	Information and communications technicians						
41	General and keyboard clerks						
42	Customer services clerks						
43	Numerical and material recording clerks						
44	Other clerical support workers						
51	Personal services workers						
52	Sales workers						
53	Personal care workers						
54	Protective services workers						
61,62	Skilled agricultural, forestry and fishery workers						
71	Building and related trades workers (excluding electricians)						
72	Metal, machinery and related trades workers						
73,75	Craft and other trades workers						
74	Electrical and electronic trades workers						
81	Stationary plant and machine operators						
82	Assemblers						
83	Drivers and mobile plant operators						
91	Cleaners and helpers						
92,93	Agricultural and manufacturing labourers						
94	Food preparation assistants						
95,96	Street, refuse and other elementary workers						

Note: The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table 3.7. Occupational imbalances in the United Kingdom from 2019-2024

		2019	2020	2021	2022	2023	2024
		Large shortage Small shortage In balance Large surplus Small surplus Unavailable					
11-14	Managers						
21	Science and engineering professionals						
22	Health professionals						
23	Teaching professionals						
24	Business and administration professionals						
25	ICT professionals						
26	Legal, social and cultural professionals						
31	Science and engineering associate professionals						
32	Health associate professionals						
33	Business and administration associate professionals						
34	Legal, social and cultural associate professionals						
35	Information and communications technicians						
41	General and keyboard clerks						
42	Customer services clerks						
43	Numerical and material recording clerks						
44	Other clerical support workers						
51	Personal services workers						
52	Sales workers						
53	Personal care workers						
54	Protective services workers						
61,62	Skilled agricultural, forestry and fishery workers						
71	Building and related trades workers (excluding electricians)						
72	Metal, machinery and related trades workers						
73,75	Craft and other trades workers						
74	Electrical and electronic trades workers						
81	Stationary plant and machine operators						
82	Assemblers						
83	Drivers and mobile plant operators						
91	Cleaners and helpers						
92,93	Agricultural and manufacturing labourers						
94	Food preparation assistants						
95,96	Street, refuse and other elementary workers						

Note: The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table 3.8. Occupational imbalances in the United States from 2019-2024

		2019	2020	2021	2022	2023	2024
		Large shortage Small shortage In balance Large surplus Small surplus Unavailable					
11-14	Managers						
21	Science and engineering professionals						
22	Health professionals						
23	Teaching professionals						
24	Business and administration professionals						
25	ICT professionals						
26	Legal, social and cultural professionals						
31	Science and engineering associate professionals						
32	Health associate professionals						
33	Business and administration associate professionals						
34	Legal, social and cultural associate professionals						
35	Information and communications technicians						
41	General and keyboard clerks						
42	Customer services clerks						
43	Numerical and material recording clerks						
44	Other clerical support workers						
51	Personal services workers						
52	Sales workers						
53	Personal care workers						
54	Protective services workers						
61,62	Skilled agricultural, forestry and fishery workers						
71	Building and related trades workers (excluding electricians)						
72	Metal, machinery and related trades workers						
73,75	Craft and other trades workers						
74	Electrical and electronic trades workers						
81	Stationary plant and machine operators						
82	Assemblers						
83	Drivers and mobile plant operators						
91	Cleaners and helpers						
92,93	Agricultural and manufacturing labourers						
94	Food preparation assistants						
95,96	Street, refuse and other elementary workers						

Note: The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

3.1.2. Occupational imbalances at the industry level

Labour and skill shortages may constrain industry growth and competitiveness, as they limit firms' productivity (McGowan and Andrews, 2017^[29]; Andrews, Égert and de la Maisonneuve, 2025^[159]). Measuring shortages at the industry level enables the identification of industries that are particularly affected, as well as the development of policies tailored to the specific dynamics of each industry. This is particularly relevant in light of the twin transition, which is reshaping skill requirements across industries. To illustrate the extent of occupational imbalances at the industry level, Figure 3.1 shows occupational imbalances by industry for the most recent year available.

In most OECD Member countries, the education industry is facing labour shortages, reflecting mounting pressures on the sector's capacity to deliver quality education. These shortages are driven largely by a lack of teachers, who constitute the largest occupational group within the industry. Difficulties in recruiting and retaining teaching staff can constrain the ability of educational institutions to meet growing and evolving student needs, increase workloads for existing staff and place additional strain on education systems. As an ageing teaching workforce increases replacement demand and further reduces the available teaching workforce, reducing teacher shortages will be critical to ensuring the long-term resilience and effectiveness of education provision.

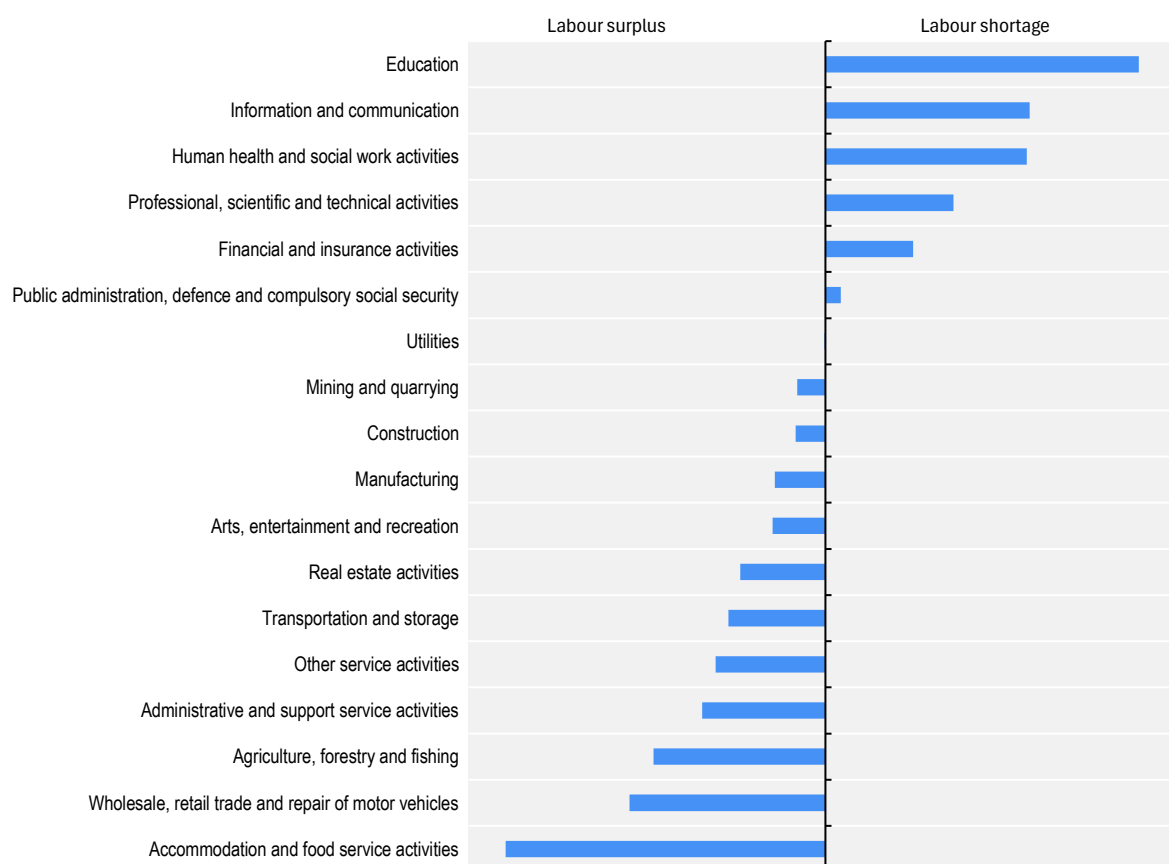
Furthermore, key industries, such as professional, scientific and technical activities and information and communication activities, face occupation shortages in the majority of countries (see Annex Table A.2 for country-level industry shortages). Results from the Global Forum on Productivity's Employer Survey also found that the ICT sector was facing the most severe shortages in 2023, suggesting that the shortages are persistent (OECD, 2024^[150]). This is concerning as these industries are key in facilitating the twin transition and occupation shortages could slow these down. In addition, these industries require high levels of human capital and industry-specific knowledge, which take time to accumulate. This implies that educating new workers for the industry would require more time, while re-skilling existing workers may prove challenging. Shortages in these industries require timely action by countries to ensure that digitalisation and their transition to a green economy is not restricted by occupation shortages.

Human health and social work activities also face significant occupation shortages in most countries, as a result of significant shortages of health professionals, health associate professionals and personal care workers. In contrast, in Luxembourg, the human health and social work activities sector is in surplus despite significant shortages of health professionals. This shows that industry-level imbalances can mask underlying occupation shortages, highlighting the importance of analysing both industry and occupational imbalances to fully understand the challenges facing specific industries and design effective policy responses.

The accommodation and food service industry is in surplus in most countries, largely because occupations such as personal service workers and food preparation assistants are in surplus relative to other occupations. In contrast, labour market tightness indicators, measured as the number of vacancies per unemployed person, point to significant shortages in the industry (Causa et al., 2025^[9]). Figure 3.2 shows each sub-indicator for personal service workers and food preparation assistants for the OECD area on average for the most recent year available. The growth in OJP does point to a shortage, as the number of OJP for personal service workers and food preparation assistants have been increasing more than for other occupations. At the same time, the high unemployment rate and low growth in hours worked compared to other occupations point to a surplus among personal service workers and food preparation assistants. This highlights that while vacancy measures are a useful indicator of recruitment difficulties, other labour market signals are also important indicators of occupational imbalances. Poor job quality and high turnover in the industry may contribute to persistent hiring difficulties despite the apparent surplus of workers (Causa et al., 2025^[9]).

Figure 3.1. Key industries face significant shortages

Occupational imbalances for the most recent year available, by industry

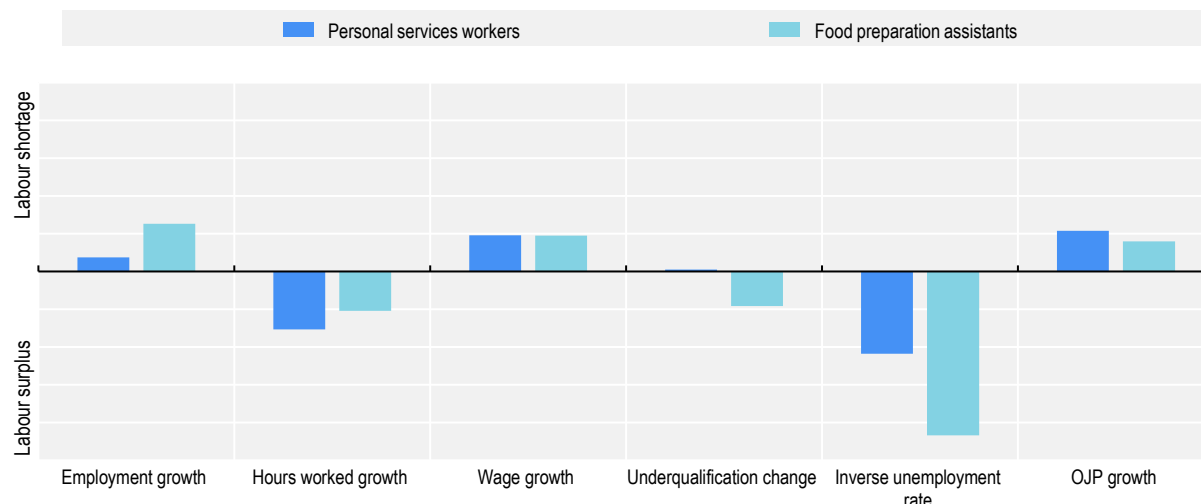


Note: The OECD average is the mean of the occupation-level indicator in the most recent year available for OECD Member countries included in the Skills for Jobs Database. The most recent year available is 2024 for most countries, exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). Annex Table A.2 shows country-level industry imbalances.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Figure 3.2. Growth in OJP and wage point to shortages for occupations in the accommodation and food services industry, while hours worked and unemployment rate point to surpluses

Sub-indicators of the Skills for Jobs Indicator for personal service workers and food preparation assistants for the most recent year available, OECD average



Note: The OECD average is the mean of the occupation-level sub-indicators in the most recent year available for OECD Member countries included in the Skills for Jobs Database. The most recent year available is 2024 for most countries, exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). Positive values indicate a shortage, while negative values indicate a surplus.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

3.2. Knowledge, abilities and skill shortages

3.2.1. Knowledge shortages

Shortages are concentrated in knowledge areas associated with high-skilled occupations, such as mathematics, computers and electronics and education and training knowledge (see Figure 3.3). This is consistent with observed shortages in high-skilled occupations, such as teaching and ICT professionals. Even in countries such as Australia and New Zealand, where ICT professionals appear to be in surplus, these knowledge areas remain in shortage (see Annex Table A.3 for country-level knowledge shortages). This may reflect an increase in the importance of digital skills for various occupations as a result of digitalisation and AI expansion (OECD, 2026_[160]).

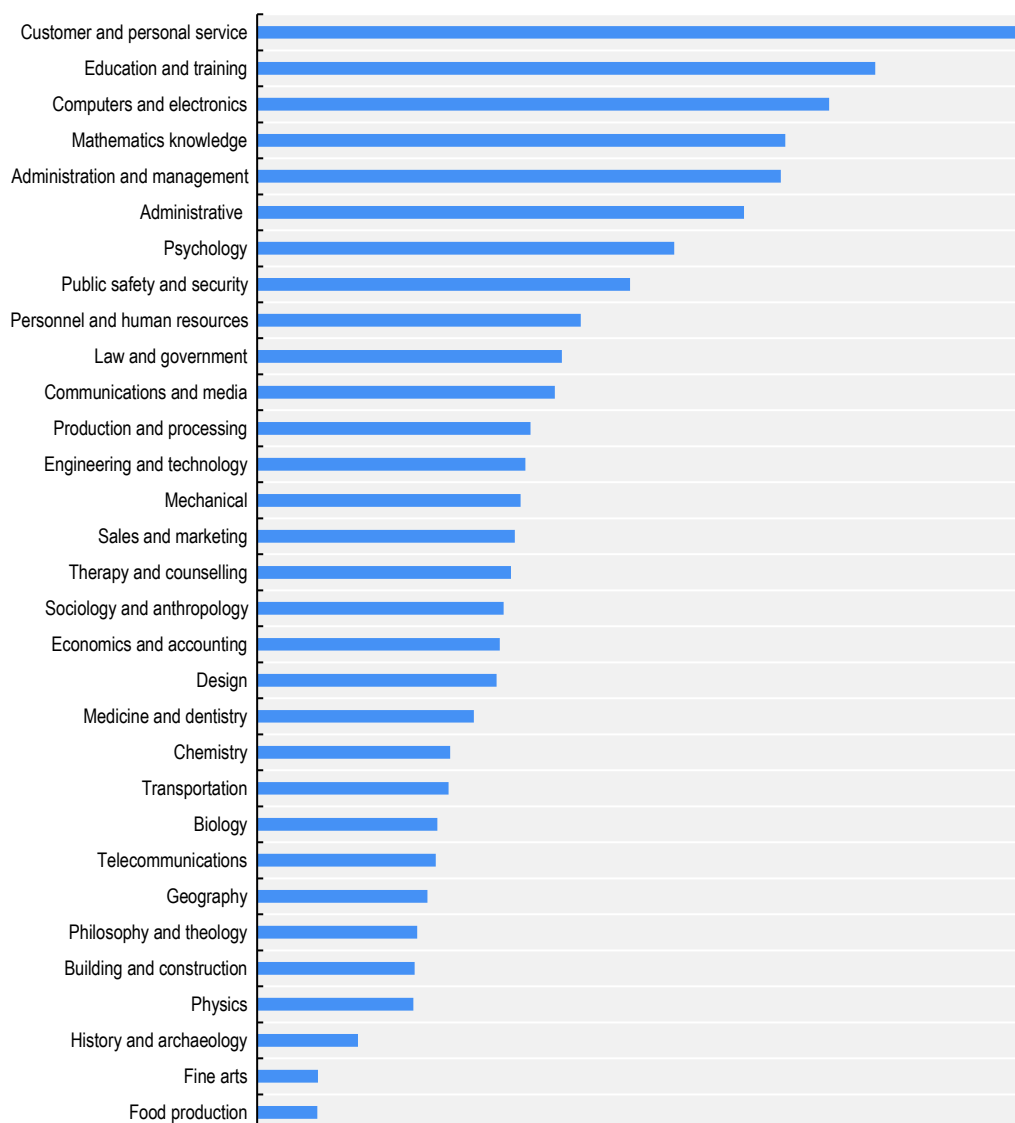
Administration and managerial knowledge is also in shortage in many countries, suggesting that demand for these skills exceeds available supply. While advances in algorithmic management may automate some managerial tasks, an OECD survey of mid-level managers in six countries (France, Germany, Italy, Japan, Spain and the United States) finds that the use of algorithmic management tools is associated with a greater need for general managerial skills, among others (Milanez, Lemmens and Ruggiu, 2025_[161]).

Administrative knowledge is in shortage in all countries (see Annex Table A.3). While AI is expected to replace routine clerical tasks, its diffusion may not yet be sufficiently advanced to produce measurable labour market effects. Moreover, residual and emerging tasks – such as managing digital systems, interpreting outputs and handling non-routine processes – continue to require human input. This suggests that any mitigating effect of AI on skill shortages is not yet visible.

Medicine and dentistry are not among the most acute knowledge shortage areas, but they remain in shortage in many countries. This aligns with persistent shortages of health professionals and health associate professionals. In some countries, such as Brazil and Italy, these knowledge areas appear to be in balance despite substantial shortages in health occupations (see Annex Table A.4). This reflects the aggregate nature of the indicator: knowledge areas very important for a small number of occupations may appear less in shortage than those important for a broader range of occupations.

Figure 3.3. Knowledge areas associated with high-skilled occupations are generally in shortage

Knowledge shortages for the most recent year available for the OECD area



Note: The OECD average is the mean of the skill-level indicator for the most recent year available for OECD Member countries included in the Skills for Jobs Database. The latest available year is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The higher the value, the larger the shortage. Annex Table A.3 presents country-level knowledge shortages.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Shortages are also evident in knowledge areas linked to middle-skilled occupations, particularly customer and personal service. This domain is in shortage in all countries. While some customer service functions are expected to be automated, personal services remain less exposed to substitution by AI and technology, as they require in-person interaction, adaptability and interpersonal skills.

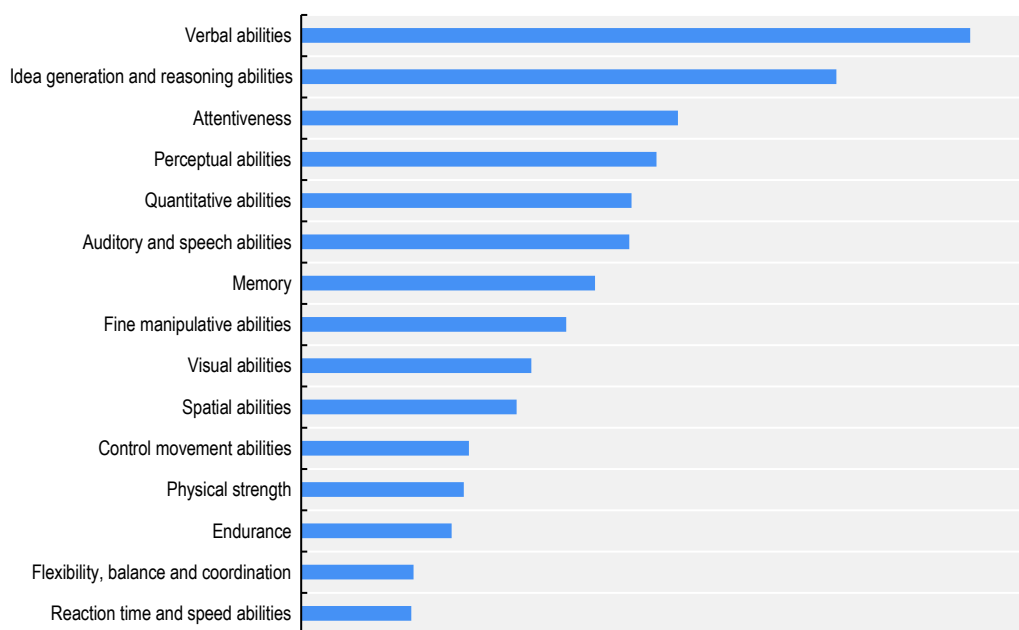
Building and construction knowledge remains broadly in balance, despite shortages of science and engineering professionals and associate professionals, as well as of trades workers, such as electrical and electronic trade workers and building and related trades workers. This could suggest that the relevant knowledge base exists, but that workers may not be willing to work in these occupations. This may reflect job quality issues – such as working conditions, job security or wages – which limit the attractiveness of these occupations and hinder the mobilisation of available skills, particularly in trade occupations.

3.2.2. Ability shortages

Cognitive abilities, such as reasoning and verbal abilities, are among the abilities most frequently in shortage (see Figure 3.4). These abilities underpin many of the skills required for work, as well as the capacity to acquire new skills (Woessmann, 2025^[53]). As a result, they are important for a wide range of occupations, contributing to the abilities being in shortage. Some of these abilities are also essential abilities, such as verbal abilities, which are needed for many occupations, including ones in surplus. This suggests that, despite indications of shortage, the overall availability of some cognitive abilities in the labour market may be more balanced than implied by the indicator.

Figure 3.4. Cognitive abilities are in shortage, while physical and psychomotor abilities are in balance

Ability shortages for the most recent year available for the OECD area



Note: The OECD average is the mean of the skill-level indicator for the most recent year available for OECD Member countries included in the Skills for Jobs Database. The latest available year is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The higher the value, the larger the shortage. Annex Table A.4 presents country-level ability shortages.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Physical and psychomotor abilities, such as control movement abilities, physical strength and endurance, are generally in balance in most countries. These abilities are generally associated with lower-skilled occupations, which are in surplus in many countries. By contrast, sensory abilities, such as visual, auditory and speech abilities, tend to be in shortage.

3.2.3. Skill shortages

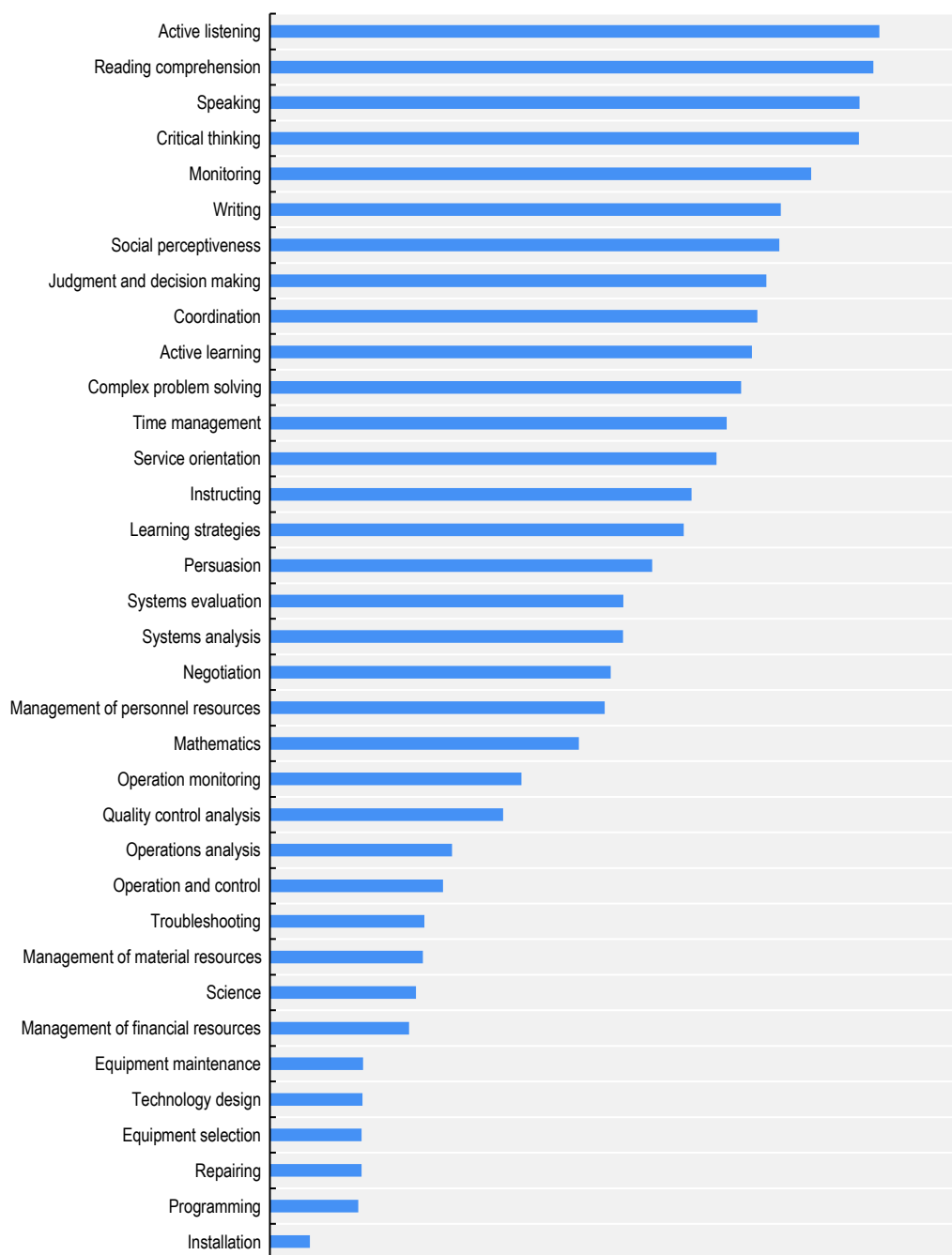
Essential skills, which are important for most occupations, are in significant shortage in OECD Member countries (see Figure 3.5). These skills include active listening, reading comprehension and critical thinking. This finding aligns with evidence from the 2023 PIAAC Survey of Adult Skills, which measures adults' literacy, numeracy and problem-solving skills, finding that around a quarter of the adult population scored at the two lowest levels of the tests (OECD, 2024^[4]). These results vary significantly between countries, ranging from around 10% in Finland to 40% in Portugal. In contrast, there is little variation between countries in the shortage of essential skills.

Social skills, including social perceptiveness, co-ordination, persuasion, negotiation, instructing and service orientation, are also in shortage in the OECD area. This aligns with the demand for social skills generally being on the rise (Deming, 2017^[70]), which can lead to shortages when supply does not increase sufficiently. One possible explanation for the growing demand is that technological advances increase the value of skills that are less amenable to automation, such as social and interpersonal skills.

Software skills, such as programming and troubleshooting, are generally in balance despite widespread shortages of ICT professionals and technicians. This may partly reflect how skill shortages are measured. Since skill shortages are calculated by aggregating information across occupations, skills that are highly important for a relatively small number of occupations may appear less in shortage than more broadly used skills, even when the underlying occupations face significant shortages. The finding that software skills appear broadly in balance should therefore be interpreted with caution. For example, employer surveys suggest that skill shortages are slowing the adoption of AI technologies, indicating that the supply of relevant technical skills may not be keeping pace with demand (OECD, 2026^[160]).

Figure 3.5. Essential, social and system skills are in shortage, while remaining skills are closer to balance

Skill shortages for the most recent year available for the OECD area



Note: The OECD average is the mean of the skill-level indicator in the most recent year available for OECD Member countries included in the Skills for Jobs Database. The latest available year is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The higher the value, the larger the shortage. Annex Table A.5 and Table A.6 present country-level skill shortages.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

3.3. Policy implications

The analysis highlights that there is no single solution to skill shortages. The drivers of shortages differ across occupations and sectors, ranging from rapid growth in demand for digital skills, to demographic pressures in healthcare, to recruitment and retention challenges linked to working conditions. As a result, policy responses need to combine measures that expand the supply of skills, support labour market transitions and improve job quality. This section lists potential policy responses, and Box 3.1 presents policy recommendations tailored to the occupations most in shortage.

Strengthen skills assessment and anticipation systems. Effective skills policies require timely information on emerging labour market needs. Strengthening skills assessment and anticipation systems can help align education and training provision with labour demand and support more efficient allocation of workers across occupations and sectors (OECD, 2016^[162]; OECD, 2026^[90]).

Strengthen initial education and adult learning. As the green transition and the adoption of AI reshape skill demand, workers increasingly require a combination of strong foundational skills and occupation-specific competencies (OECD, 2023^[163]). While the latter may need to be updated repeatedly over the life course, strong foundational skills support continuous learning, adaptability and the acquisition of new technical skills as job requirements evolve (Woessmann, 2025^[53]). Developing these skills requires strong initial education systems alongside accessible, high-quality adult learning opportunities (OECD, 2023^[163]; OECD, 2026^[164]; OECD, 2026^[165]). Micro-credentials can contribute by lowering barriers to participation in learning and enabling workers to acquire new competencies throughout their careers (OECD, 2024^[166]).

Create flexible pathways into occupations facing persistent shortages. Expanding career and training pathways can help attract workers into occupations where labour demand is expected to remain strong. In healthcare, flexible learning pathways and support for career transitions can broaden the available talent pool (OECD/ILO, 2026^[167]). In education, flexible entry routes and programmes for second-career teachers can help reduce persistent teacher shortages (OECD, 2025^[158]).

Promote skills-first hiring approaches. Skills-first hiring approaches prioritise demonstrated competencies over traditional qualifications, enabling employers to access broader talent pools and adapt more dynamically to evolving skill needs, particularly in rapidly changing sectors such as technology (OECD, 2024^[166]).

Strengthen career guidance to support transitions into shortage occupations. Providing timely information on employment prospects, skill requirements and training opportunities can encourage both young people and mid-career workers to enter occupations facing persistent shortages. This can help expand talent pipelines into these occupations and improve the responsiveness of labour supply to changing skill needs (OECD, 2021^[168]; OECD, 2022^[169]).

Improve job quality in shortage occupations. Persistent shortages are often linked not only to insufficient skill supply but also to difficulties attracting and retaining workers. Improving job quality, including working conditions, work-life balance and occupational health, can help mitigate shortages in sectors characterised by shift work, physical strain and elevated mental health risks (OECD, 2023^[155]; Causa et al., 2025^[9]; OECD, 2025^[156]).

Support labour mobility while strengthening international co-ordination. Labour shortages often differ between countries, creating opportunities for labour mobility to improve the matching of workers to jobs. Within Europe, policies that facilitate the recognition of qualifications, improve information on job opportunities and support worker mobility through instruments, such as EURES, can help alleviate shortages in occupations and sectors where labour demand exceeds local supply (European Labour Authority, 2026^[7]). However, mobility is less effective where shortages are widespread across countries, as is the case for health professionals. In such occupations, cross-border mobility can alleviate shortages in destination countries while exacerbating them in countries of origin, particularly in parts of Eastern and

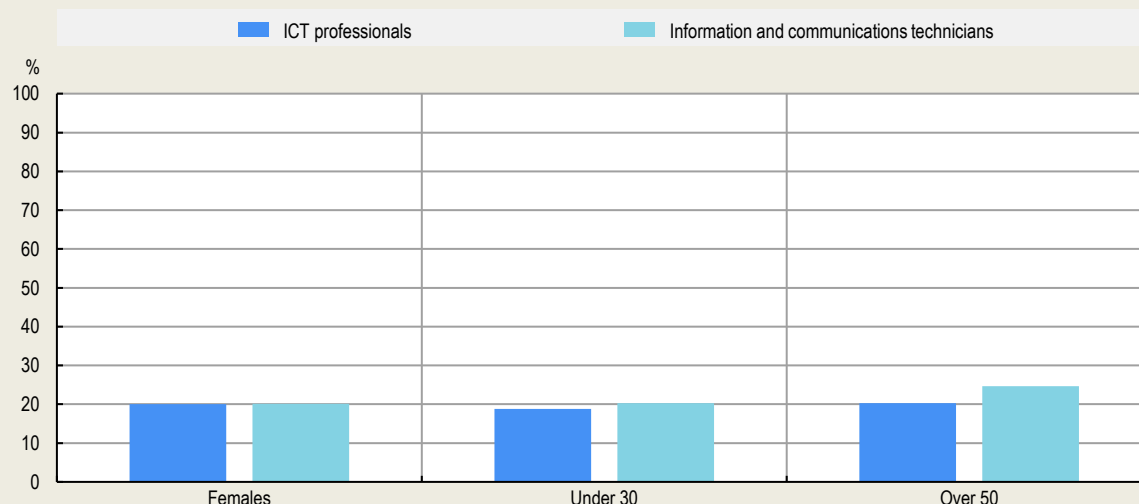
Southern Europe that experience significant outflows of doctors and nurses (OECD, 2025^[170]; WHO Regional Office for Europe, 2025^[171]). Mitigating these shortages therefore requires co-ordinated approaches that combine mobility policies with investments in domestic training capacity, workforce planning and retention.

Box 3.1. Policy recommendations for occupations facing the greatest shortages in OECD Member countries

ICT professionals, as well as **information and communications technicians**, are among the occupations facing the greatest shortages. These shortages are likely linked to digitalisation of economies and the rapid development of AI technologies, as labour supply has struggled to keep pace with growing demand (OECD, 2016^[172]; Squicciarini and Nachtigall, 2021^[173]; Borgonovi et al., 2023^[174]). The share of women in these occupations is very low (only 20% in OECD Member countries – see Figure 3.6), which suggests potential to tackle these shortages by increasing participation among under-represented groups. In addition, information and communications technicians tend to have a relatively older workforce, indicating a need to strengthen talent pipelines to replace workers approaching retirement. Reducing these shortages will require broadening the supply of ICT talent through career guidance, skills-first hiring practices, flexible learning pathways and micro-credentials, as well as designing education and training courses to respond to rapidly changing skill needs (OECD, 2024^[166]).

Figure 3.6. Low representation of women among ICT professionals and technicians

Share of females, under 30 and over 50 among ICT professionals and information and communications technicians



Note: The statistics include Austria, Belgium Flanders, Canada, Chile, the Czech Republic (Czechia), Denmark, England, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Korea, Lithuania, Latvia, the Netherlands, Norway, New Zealand, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland and the United States.

Source: PIAAC Survey of Adult Skills 2023.

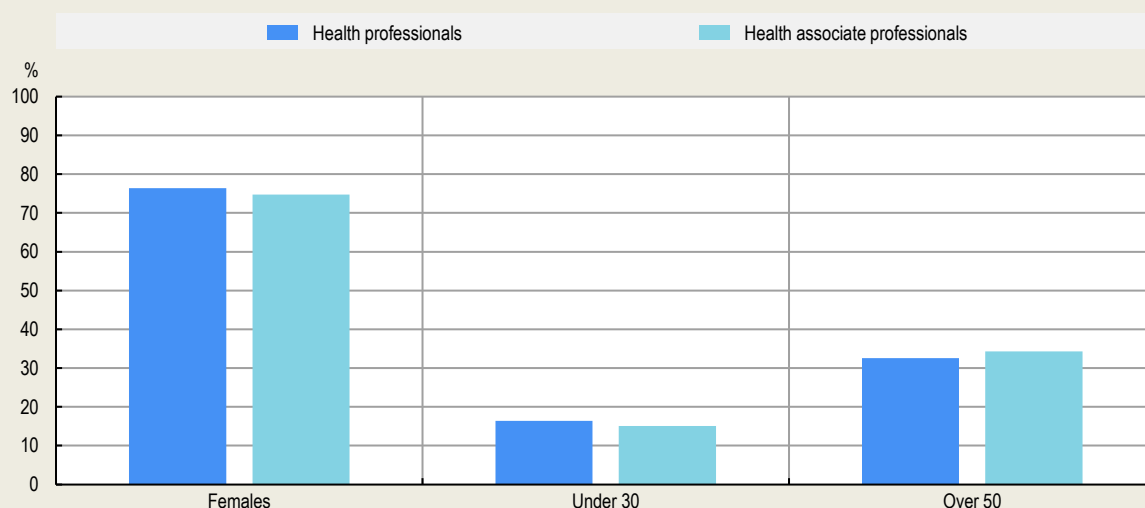
Health professionals and health associate professionals have been in persistent shortage in OECD Member countries over the last two decades, reflecting a structural imbalance as labour supply has not kept pace with rising demand for healthcare services, resulting from growing care needs and population

ageing (OECD/European Commission, 2024^[154]). Retention challenges linked to demanding working conditions have further exacerbated these shortages (OECD, 2023^[155]; Causa et al., 2025^[9]; OECD, 2025^[156]). These shortages may intensify as a sizeable share of the healthcare workforce approaches retirement age: around 30% of workers in these occupations are aged over 50, while less than 20% are under 30 (see Figure 3.7).

Mitigating these shortages requires educating more health professionals and health associate professionals and improving working conditions (OECD, 2023^[155]). Expanding participation among under-represented groups could contribute to these efforts, particularly among men, who account for less than 30% of employment in these occupations (see Figure 3.7). However, health professionals currently have, on average, more than 16 years of education, implying that expanding the supply of qualified workers is likely to take considerable time (OECD, 2024^[4]). Complementary measures, such as expanding flexible learning and career pathways into healthcare occupations, including for workers transitioning from other sectors, can help broaden the available talent pool (OECD/ILO, 2026^[167]).

Figure 3.7. Low representation of men and younger workers among health professionals and health associate professionals

Share of females, under 30 and over 50 among health professionals and health associate professionals



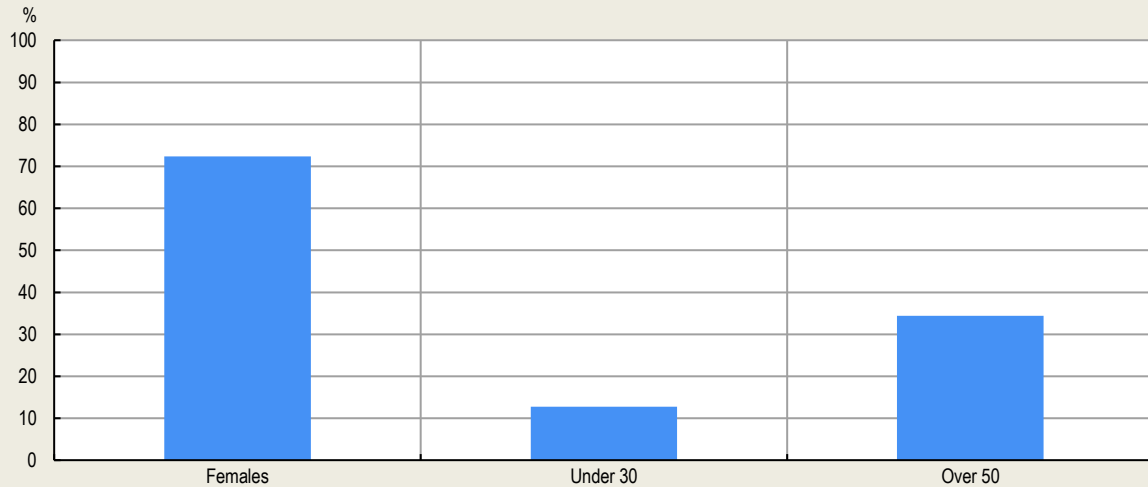
Note: The statistics include Austria, Belgium Flanders, Canada, Chile, Czechia, Denmark, England, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Korea, Lithuania, Latvia, the Netherlands, Norway, New Zealand, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland and the United States.

Source: PIAAC Survey of Adult Skills 2023.

Teaching professionals, like health professionals, have been in persistent shortage in many OECD Member countries, and these shortages will likely intensify as a sizeable share of the workforce approaches retirement age. More than 30% of teachers are aged over 50, compared with only around 10% aged under 30 (see Figure 3.8). In addition, teachers have, on average, more than 16 years of education, implying that educating more teachers is unlikely to alleviate shortages in the short term (OECD, 2024^[4]; OECD, 2025^[158]). Reducing these shortages will therefore require measures to facilitate entry into the profession, including through flexible learning pathways and opportunities for mid-career transitions (OECD, 2025^[158]). Educating more teachers and expanding participation among under-represented groups can contribute to reducing shortages in the long-term.

Figure 3.8. Teaching professionals include relatively few men and younger workers

Share of females, under 30 and over 50 among teaching professionals



Note: The statistics include Austria, Belgium Flanders, Canada, Chile, Czechia, Denmark, England, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Korea, Lithuania, Latvia, the Netherlands, Norway, New Zealand, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland and the United States.

Source: PIAAC Survey of Adult Skills 2023.

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Annex A. Supporting material

Overview of data and country specific indicator specifications

Table A.1. Overview of data and country-specific indicator specifications

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Argentina	Permanent household survey	2017	2024	11-14 61, 62 95, 96	✓	✓	✓	✓	✓	
Australia	Labour force survey Median hourly wage: Survey of Employee Earnings and Hours OJP: Lightcast data	2016	2025	11-14, 62, 92 and 95 excluded	✓	✓	✓	✓	✓	✓
Austria	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Belgium	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Brazil	National household sample survey – continuous	2013	2024	61, 62	✓	✓	✓		✓	
Bulgaria	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Canada	Labour force survey OJP: Lightcast data	2001	2024	11-14 61, 62 81, 82 95, 96	✓	✓	✓		✓	✓
Chile	Encuesta Nacional de Caracterización Socio-económica (CASEN)	2001	2022	11-14 34, 36 81, 82 94 excluded	✓	✓	✓		✓	
Cyprus	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Czechia	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Denmark	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	
Estonia	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	
Finland	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
France	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2013	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Germany	European labour force survey Median hourly wage: German socio-economic panel OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Greece	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	
Hungary	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Ireland	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Italy	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Korea	Korean Labor & Income Panel Study (KLIPS) OJP: Occupational Labor Force Survey at Establishments	2010	2023	11-14 92, 93 95, 96 60 excluded	✓	✓	✓		✓	✓
Latvia	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	
Lithuania	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Luxembourg	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Mexico	The National Survey of Occupation and Employment (ENOE). From April to June 2020, Telephone Survey of Occupation and Employment (ETOE) was used, and from June to December 2022, the National Survey of Occupation and Employment, New Edition (ENOE ^N).	2006	2024		✓	✓	✓		✓	
Netherlands	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2009	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
New Zealand	Labour force survey OJP: Lightcast data	2017	2025		✓	✓	✓		✓	✓
Norway	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2022	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓		✓	
Peru	National household survey (ENAHO)	2008	2024	11-14 24, 25 53, 54 61, 62 81, 82	✓	✓	✓		✓	

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Poland	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Portugal	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Romania	European labour force survey Median hourly wage: EU statistics on income and living conditions	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	
Slovak Republic	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2023	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Spain	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓

Country	Data source(s)	Time period		Merged occupations	Indicators included in composite indicator					
		First year	Final year		Wage	Hours worked	Number of employed	Inverse unemployment rate	Under-qualification rate*	Online job postings
Sweden	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Switzerland	European labour force survey Median hourly wage: EU statistics on income and living conditions OJP: Lightcast data	2008	2023	11-14 61, 62 73, 75 92, 93 95, 96	✓	✓	✓	✓	✓	✓
Türkiye	Labour force survey	2015	2023		✓	✓	✓		✓	
United Kingdom	Labour force survey OJP: Lightcast data	2007	2024	11-14 61, 62 73, 75 81, 82 92, 93 95, 96	✓	✓	✓	✓	✓	✓
United States	Current population survey (CPS) OJP: Lightcast data	2004	2024		✓	✓	✓	✓	✓	✓

Note: OJP stands for online job postings. Data from the European Labour Force Survey is taken from Eurostat (2006-2024_[175]); and data from the EU statistics on income and living conditions is taken from Eurostat (2004-2025_[176]). *underqualification is excluded for some occupations when the modal education level is the lowest level of education.

Source: OECD elaboration.

Overview of data breaks

This section presents an overview of major data breaks in the data underlying the *OECD Skills for Jobs Database* (OECD, 2026^[153]). The section first presents data breaks for the EU Labour Force Survey and the EU statistics on income and living conditions, followed by a breakdown by country.

EU-Labour Force Survey

Change in measure of labour force status and methodology in 2021. The size and direction of the breaks vary by country. Based on visual inspection of the time-series, the following countries and occupations are adjusted backwards using the country-level growth rate in the break year and the growth rates of the pre-break series for earlier years:

- Belgium: Occupation 32, 41 and 44
- Denmark: Occupation 23
- France: Occupation 24 and 31
- Spain: Occupation 51 and 52

More information about the breaks is reported in the national documentation on Eurostat's website, see:

[https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_Labour_Force_Survey - new methodology from 2021 onwards](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_Labour_Force_Survey_-_new_methodology_from_2021_onwards).

Germany integrated the EU-LFS into a new microcensus as a subsample in 2020. This, combined with the impact of the COVID-19 pandemic, led to significant breaks in the time series. All occupations were backwards adjusted from 2020. Read more about the break here:

<https://ec.europa.eu/eurostat/documents/10186/6246844/LFS-2020-Note-on-German-data.pdf>.

Education variables were affected by changes in the questionnaire and survey process in France in 2013. Underqualification was backwards adjusted.

In 2013, the Netherlands switched to online interviews which led to changes in the elicitation of occupation information. All occupations were adjusted backwards in 2013.

In 2012, there was a change in the national occupation classification in Germany. This led to visible breaks in the time series for occupations 41 and 43, which were adjusted backwards.

In 2011, many EU-labour force surveys underwent significant changes leading to breaks in the data series. All data series were adjusted backwards.

Improvements in the classification of occupations in Czechia in 2010 led to visible data breaks for underqualification of occupations in ISCO major group 2. These were backwards adjusted.

EU Statistics on income and living conditions

In 2024, there was a methodological break for the Slovak Republic due to using administrative data to complement the survey. This led to visible breaks in median hourly wage from 2023 and 2024. For this reason, 2024 data is excluded for the Slovak Republic.

EU-SILC switched from ISCO-88 to ISCO-08 in 2011, which led to breaks in the median hourly wage in 2010 as individuals are asked about their income in the year before the survey. The wage was backwards adjusted for all countries.

Argentina (Permanent household survey)

Due to errors in sampling framework, population weights from 2016 to 2018 were adjusted by coefficients provided by the Instituto Nacional de Estadística y Censos (indec). For more information see here: https://www.indec.gob.ar/ftp/cuadros/menusuperior/eph/EPH_nota_metodologica_1_trim_2019.pdf.

Chile (Encuesta Nacional de Caracterización Socio-económica – CASEN)

There were significant changes to the CASEN survey in 2022. Size of break is not clear as data for 2024 was not available at time of analysis.

Korea (Korean Labor & Income Panel Study – KLIPS)

Included additional households in the survey in 2018 to improve representativeness. Based on visual inspection, the data series was not adjusted.

Mexico (The National Survey of Occupation and Employment – ENOE)

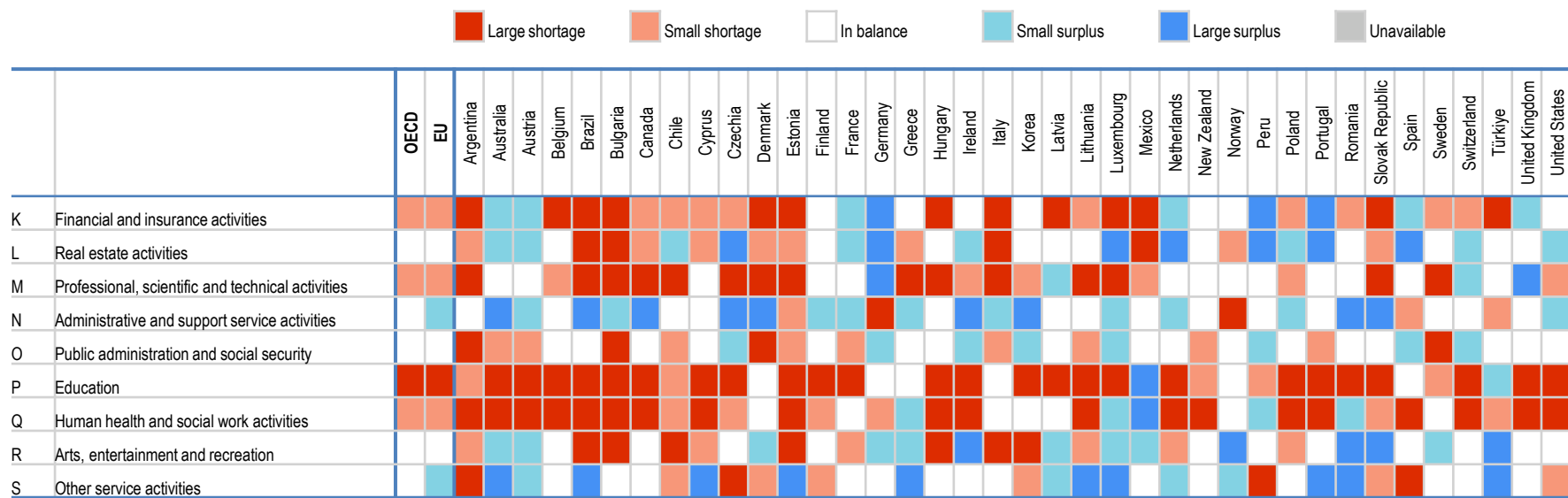
During the COVID-19 pandemic, field surveys changed to telephone surveys from April to June 2020, whereafter the survey was replaced by the National Survey of Occupation and Employment, New Edition until 2022. From 2023, data collection reverted to the National Survey of Occupation and Employment. During the COVID-19 pandemic, the sampling frequency increased with some individuals sampled once per month rather than every quarter. For these individuals, the last observation of each quarter was kept. Beyond this there were no visible breaks as a result of the change in survey vehicle.

In 2012, a new occupation classification was adopted, SINCO 2011. Based on visible inspection, underqualification was backwards adjusted in 2012.

Country-level results for industry and skill level shortages

Table A.2. Occupational imbalances for the latest available year, by industry and country

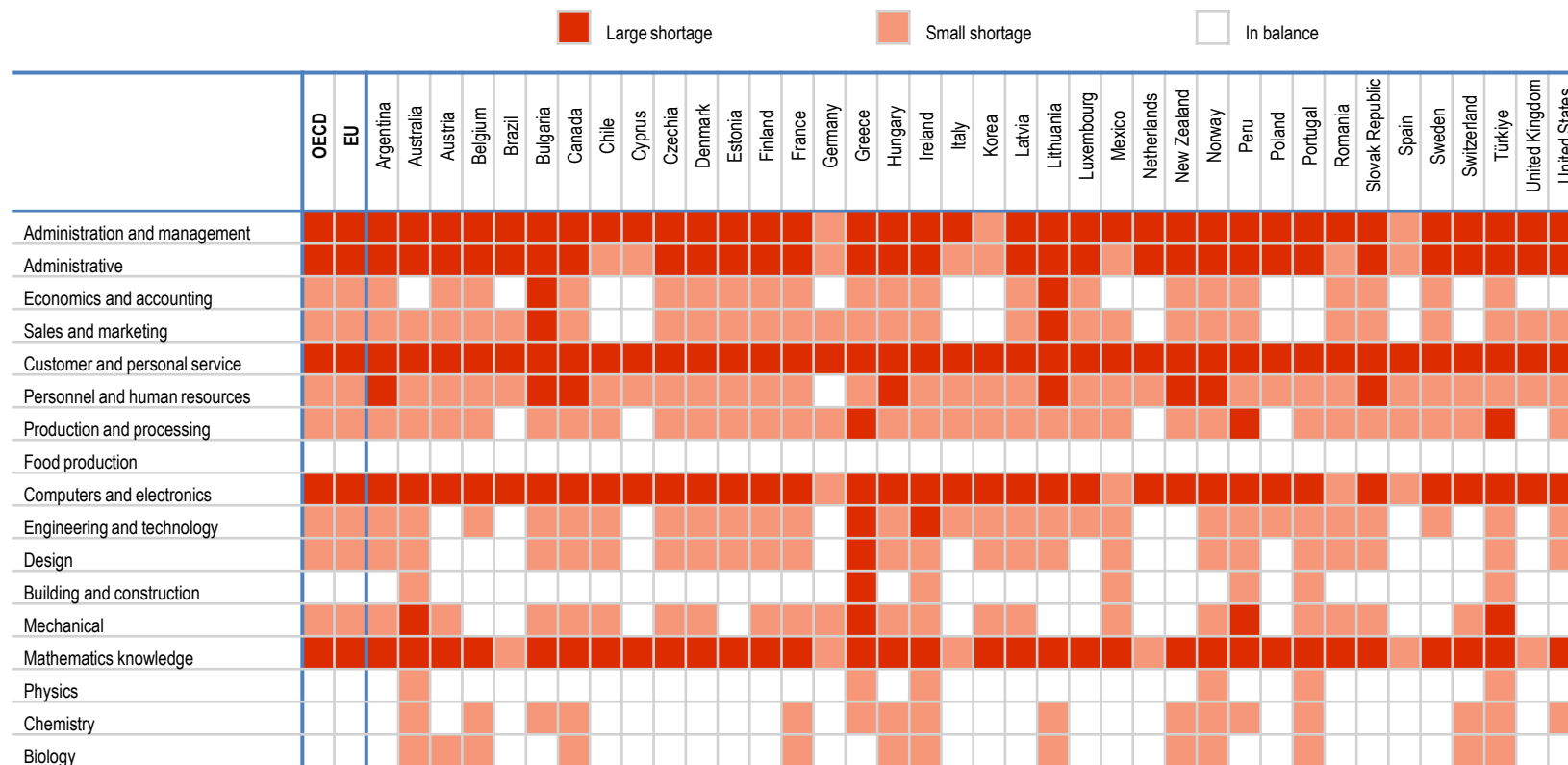
[illegible]

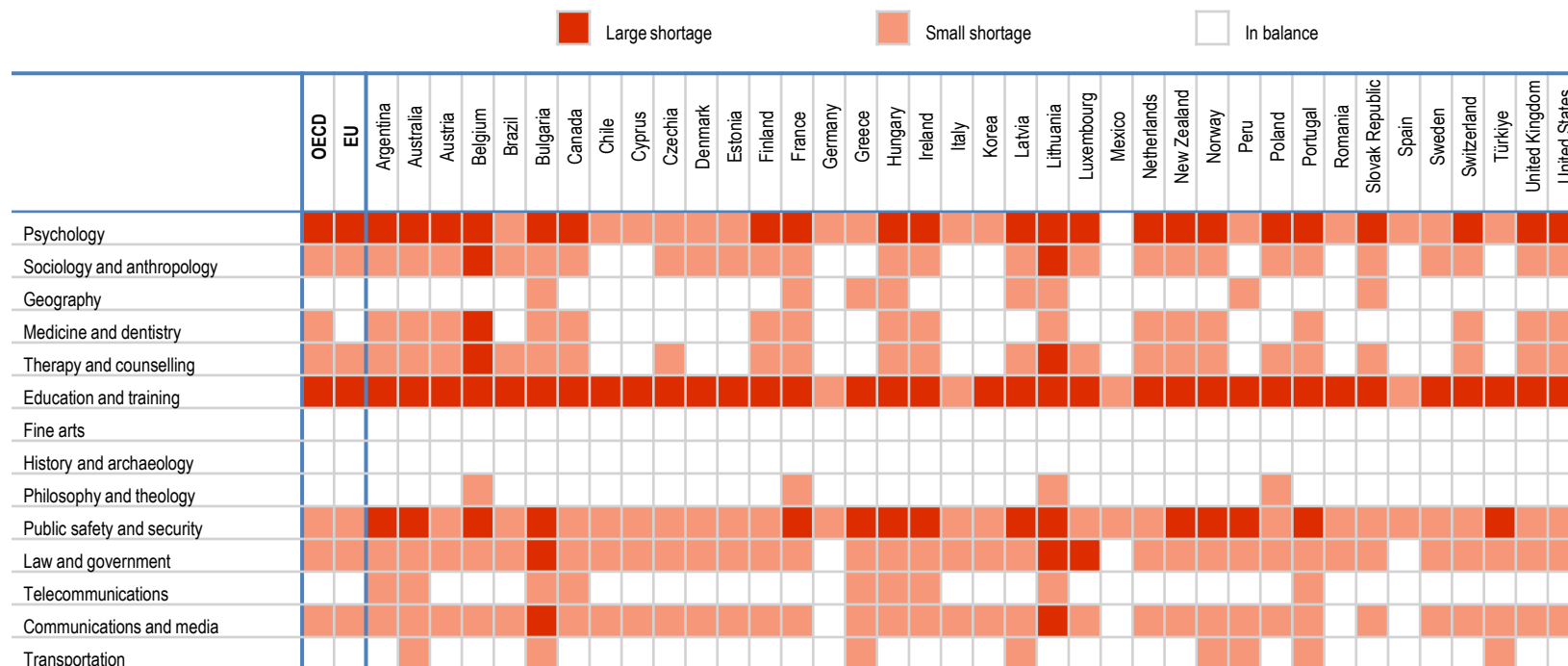


Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the industry-level indicator in the latest year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with large surplus being below the 20th percentile, small surplus being between the 20th and 40th percentile, in balance between the 40th and 60th percentile, small shortage between the 60th and 80th percentile and large shortage above the 80th percentile.

Source: OECD (2026_[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table A.3. Knowledge shortages for the latest available year, by country

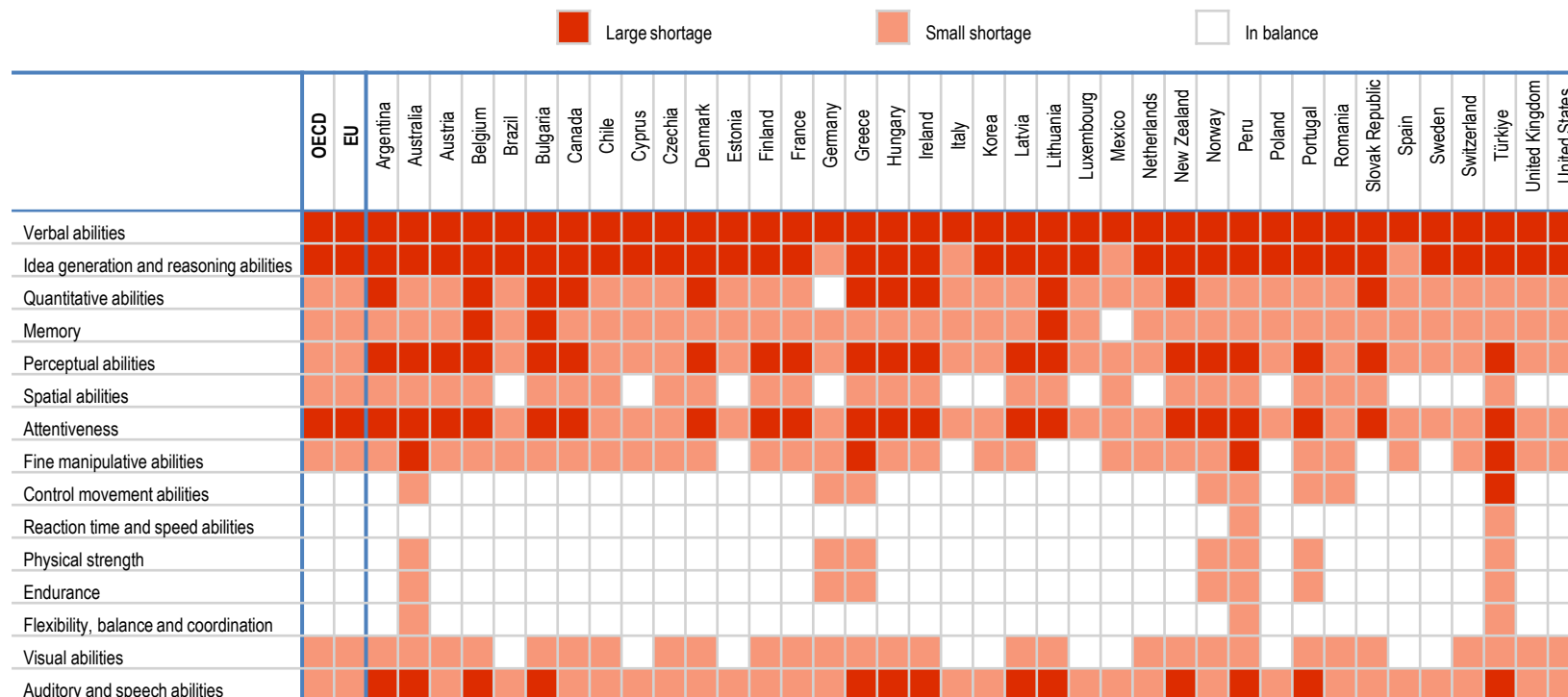




Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the skill-level indicator in the latest available year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with in balance being shortages below the 33 percentile, small shortage being shortages between the 33 and 66 percentile and large shortages being shortages above the 66th percentile.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table A.4. Ability shortages for the latest available year, by country



Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the skill-level indicator in the latest available year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with in balance being shortages below the 33 percentile, small shortage being shortages between the 33 and 66 percentile and large shortages being shortages above the 66th percentile.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table A.5. Shortages of essential skills for the latest available year, by country

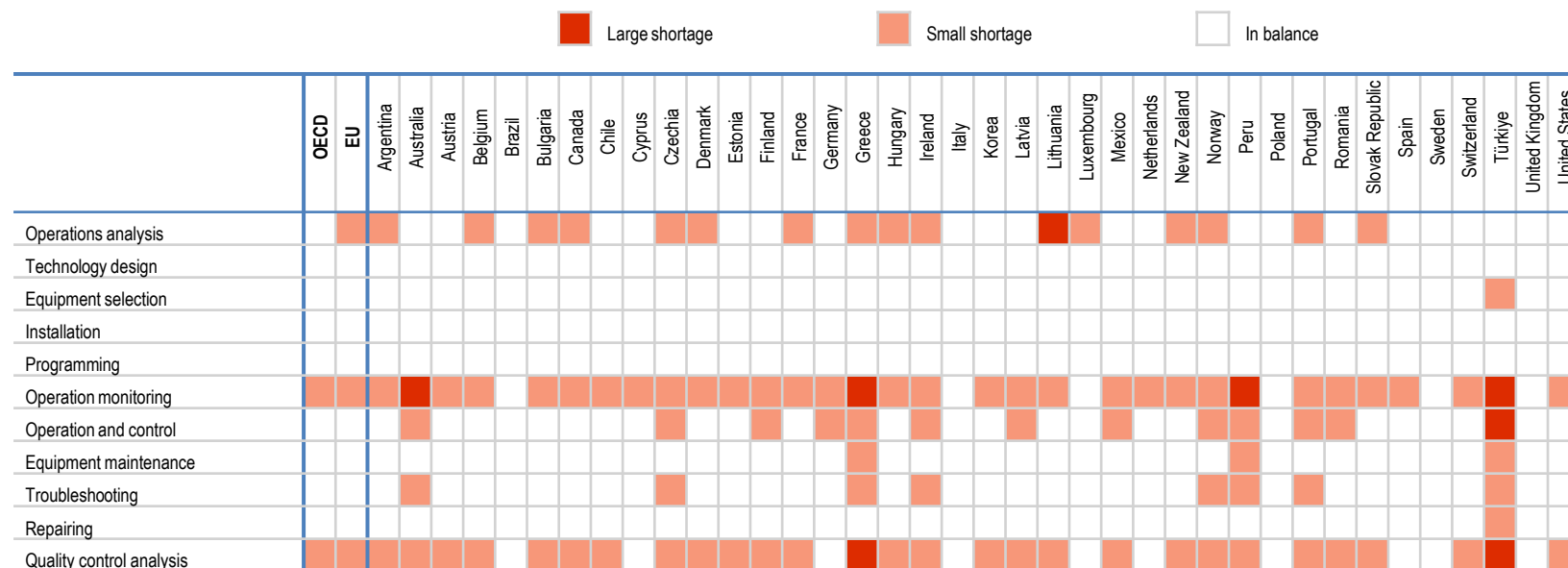


Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the skill-level indicator in the latest available year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with in balance being shortages below the 33 percentile, small shortage being shortages between the 33 and 66 percentile and large shortages being shortages above the 66th percentile.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Table A.6. Shortages of transferable skills for the latest available year, by country





Note: The most recent year available is 2024 for most countries. Exceptions are Chile and Norway (2022); Korea, the Slovak Republic, Switzerland and Türkiye (2023); and Australia and New Zealand (2025). The OECD average is the mean of the skill-level indicator in the latest available year for OECD Member countries included in the Skills for Jobs Database, and the EU average is the mean for EU countries included in the database. The categorisation is based on the percentiles for the OECD average from 2019 to 2025, with in balance being shortages below the 33 percentile, small shortage being shortages between the 33 and 66 percentile and large shortages being shortages above the 66th percentile.

Source: OECD (2026^[153]), *OECD Skills for Jobs Database 2026*, www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Notes

¹ Since Lightcast data is only available from 2025 for Korea, information on job openings from the Occupational Labor Force Survey at Establishments is used instead. It covers all industries, except agriculture, forestry and fishing, and asks employers about the number of vacancies for which the establishment is actively recruiting.

² ISCO category Subsistence Farmers, Fishers, Hunters and Gatherers (63) is excluded from the indicator, as subsistence producers are not classified as employed under the ILO definition, which limits employment to work performed for pay or profit.

³ The *OECD Skills for Jobs Dashboard* is available here:
www.oecd.org/en/data/dashboards/skills-for-jobs.html.

Mapping Skill Shortages in OECD Countries

New Evidence from the Updated Skills for Jobs Database

Although labour shortages have eased from their post-pandemic peak, employers continue to report difficulties hiring workers with the right skills. These skill imbalances are expected to intensify. Population ageing will shrink the workforce, while digitalisation, AI and the green transition are rapidly reshaping skill needs. Addressing the gap between the skills employers need and those workers possess requires timely and accurate data. The OECD Skills for Jobs database provides a harmonised and objective measure of skill imbalances in 38 countries. The results reveal persistent and widespread occupational imbalances across OECD labour markets. Shortages are particularly pronounced in high-skilled occupations, such as ICT specialists, science and engineering professionals, health professionals, and teachers. By contrast, lower-skilled occupations are more frequently characterised by labour surpluses. These patterns highlight the growing polarisation of labour market pressures and underline the urgency of policies aimed at improving skill matching and workforce adaptability.



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