Global skills gaps measurement and monitoring: Towards a collaborative framework

Technical paper prepared for the 1st meeting of the Employment Working Group under Indian presidency

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Executive Summary

Technological advancement, globalization, climate change and demographic shifts, against the backdrop of the COVID-19 pandemic and cost-of-living crisis, are impacting skill needs and exacerbating skill mismatches. Strengthening the evidence base to inform skills policies requires accurate labour market information and intelligence. However, observing and measuring the actual skills that workers possess or require is difficult and expensive, therefore proxy indicators are usually used. This paper proposes a set of basic and extended indicators to facilitate the collection and improve the quality and comparability of the data on skills and skills imbalances across G20 countries.

A set of basic indicators (Annex A, Table 1) derives from labour force surveys compiled by national statistical offices, harmonised and published by the ILO. Some of these indicators are of a contextual nature, while others measure different types of skills mismatches or add the measurement elements. The usage of the suggested set of basic indicators has the benefits of being widely available, statistically representative and internationally comparable. However, the quality of collected indicators across countries is not even, and the availability at a more granular level is poor. From the basic set of indicators, the lack of available data on wages of employees is the most acute followed by data on the time-related underemployment rate, long-term unemployment rate, share of youths not in employment, education or training (NEET rate), qualification mismatch, employment by occupations (ISCO 3-4 digits) and weekly hours worked. Finally, a composite method for deriving comparable measures of skill imbalances at a detailed level is presented, which underlies the Skills for Jobs databases of the ILO and OECD.

An extended set of indicators (Annex A, table 2) can help assess the extent to which the skills of persons in employment correspond to the job requirements. However, the surveys underlying these indicators do not cover all G20 countries and all aspects of skill gaps. A collection of these indicators in a comparable manner for G20 countries could be useful.

A short analysis to demonstrate the use of some indicators shows the complexity of skills mismatches, their high presence in G20 countries and the need for diverse policy measures to address different types of skill challenges. Policies often tend to focus mostly on the supply side and aim to enhance the responsiveness of training systems to changing labour market needs. Such policies are certainly valuable; however, to properly address overqualification and skills underutilisation, they should be accompanied by measures to foster decent jobs creation and strengthen job quality.

As there is no ideal method to assess current or anticipate future skill needs, it is considered a good practice to use a combination of various methods, both quantitative and qualitative. Big data analytics of real time online job vacancies present many challenges but also a great potential to develop and complement existing labour market information, uncovering skill trends by occupations and sectors at a very granular level. The advent of highly capable technologies such as machine learning and natural language processing, as well as the exponential growth in data availability, generate interest and efforts to achieve coherence across national and regional taxonomies or develop a global taxonomy. To enable G20 countries to communicate with one another using a common language with respect to skills, there is an urgent need to develop a global skills taxonomy, broad enough to be applied to the realities across different countries and yet detailed enough to capture skills and competencies needs.

Beyond developing skill taxonomies, an important aspect of effective skills anticipation systems is to create institutional platforms and develop capacities to generate, collect, use and disseminate data, as well as to formulate, monitor and evaluate evidence-based policies. For skills anticipation and labour market intelligence to have an impact, it is essential to involve ministries, training designers and providers, social partners and other relevant stakeholders, and have their inputs well-coordinated.

▶ 1. Introduction

The transformational forces of technological advancement, globalization, climate change, demographic shifts and migration, combined with socio-economic uncertainties due to the ongoing multiple crises are all impacting skills needs and exacerbating skill mismatches. The speed at which the world of work is changing raises challenges for policymakers in G20 countries and requires changes in the way, in which education and skills development are designed, provided and accessed. Education and skills systems in G20 countries are facing a multifaceted challenge: providing young people with a broader set of skills so that they can enter, navigate and be resilient in fast evolving labour markets and reskilling/upskilling existing workers to facilitate their labour market transitions and adaptation to changes in the workplaces. While a number of policy instruments are available to policymakers to reduce skills mismatches, having accurate labour market information and intelligence about the current and future skill demand and supply is key.

The pandemic has accelerated remote work, online learning, the platform economy and some pre-existing workplace trends such as searching for meaning and more flexibility, which has led to recent trend of "the great attrition"- sometimes called as "the great resignation", particularly in higher-income G20 countries. As a result, the competition for talent is different now. Employers need to redefine their strategies to attract and retain talent and build a value proposition that takes employees' and candidates' concerns into account.

Meanwhile, the on-going geo-political tensions and resulting in surge of energy and commodity price plunged the global economy into a stagflation scenario (ILO, 2023 and OECD, 2022), significantly deteriorating the outlook for employment. The cost-of-living crisis is making the consequences of job losses even more serious and the need for successful labour market transitions an urgent issue.

▶ 2. Skill mismatches

2.1 Types of skills mismatches

Skills mismatches refer to various types of imbalances between skills and qualifications available on the labour market and those required in jobs. The concept is broad and includes a number of distinct types of imbalances, both qualitative and quantitative. The types of skill mismatches include skill shortages, qualification mismatch, skill gaps, skill obsolescence, and over/underskilling. Mismatches can be horizontal (field of study mismatch) and/or vertical (over/underqualification). These various forms of skills mismatches are very different in terms of how they manifest themselves, how they are measured, what causes them and how their consequences are felt. In addition, the various forms of skills mismatches may co-exist, making the picture of skills mismatches even more complex (ILO, 2019, Montt 2015).

Policies that address skills mismatches tend to focus mostly on the supply side and aim to enhance the responsiveness of the education and training systems to changing labour market needs. Such policies are certainly valuable; however, to properly address overqualification and low skills utilisation, widely present in G20 countries (see 3.3.1), they should be accompanied by measures to foster decent job creation and boost job quality.

2.2 Impact of skills mismatches on labour market outcomes

The consequences of skills mismatches are felt by all actors. At the individual level, mismatch leads to serious wage penalties, especially for overqualification, that eventually affect both work and life satisfaction. For enterprises, skills mismatches have negative consequences for productivity and workforce turnover, undermining the introduction of new products, services or technologies. For countries and regions, skills mismatches can increase unemployment, and weaken attractiveness for investors. In addition, skills mismatches may also translate into a loss in returns on investments in education (public and/or private) if individuals are unable to put the skills they have developed to productive use. The extent and nature of skill mismatches vary across G20 countries, depending on country contexts (see section 3.3.). Given these implications, country-specific assessments of skill needs and mismatches are urgently needed to inform strategic responses.

▶ 3. Skills taxonomies and approaches for measuring skills gaps in G20 countries

3.1 Existing skills needs anticipation methods, approaches and limitations

There are various available tools and methods for assessing and anticipating skills needs, each with its own requirements in terms of data and technical expertise. The methods and approaches were discussed in the ILO-OECD report Approaches to anticipating skills for the future of work prepared for G20 EWG in 2018 (ILO-OECD, 2018). The report provides a detailed account on different quantitative and qualitative methods and approaches, their strengths and weaknesses and examples from many G20 countries (ILO-OECD, 2018) and should be read in conjunction to this paper. A key conclusion from the report was that, given that each method has its own strengths and weaknesses, it is considered a good practice to use a combination of various methods, both quantitative and qualitative, in order to achieve robust and reliable results.

3.2 Taxonomies

3.2.1 Available national and regional skills taxonomies

To anticipate skills needs and match them to education, training and occupations, policymakers and practitioners need to use a common language. The establishment of a measurable and coherent categorization of skills is essential. In the past decade, there has been a surge in efforts to develop skill taxonomies, i.e. classifications of skills, systematically showing their relations to education and training (qualifications) and the world of work (jobs, occupations). Most notable examples of such taxonomies can be identified in Australia, Canada, the European Union, Singapore, the United Kingdom and the United States.

▶ Table 1. Examples of National and Regional Taxonomies

	Occupational Information Network (O*NET)	European Skills, Competencies, Qualifications and Occupations (ESCO)	UK Skills Taxonomy	Singapore Skills Taxonomy (SST)	Australian Skills Classification (ASC)	Canada Skills and Competency Taxonomy
Approach	Quantitative and Qualitative	Quantitative and Qualitative	Quantitative (Data-driven)	Quantitative and Qualitative	Quantitative and Qualitative	Quantitative and Qualitative
Data source	Analysts' input; Surveys to job incumbents and employers	Collaboration between sectoral and occupational experts, review of existing classifications and qualifications, desk research by main trend by sector, job adverts and CVs	Online job adverts in the UK	Collaboration between stakeholders from various sectors on vision, transformation, occupation and skill needs, education institutions, unions and Government In progress Development of Job Skills Repository using data from foresight exercises, online job adverts and CVs, census, Skills Frameworks, training consumption and supply data	O*NET; Australian Employability Skills Framework; Employer surveys; Job adverts; Education and training course documentation	Career handbook, Skills and Knowledge Checklist, Essential Skills profiles, O*NET, Stakeholder consultations; Surveys to job incumbents and employers; Online job adverts
Developer / Owner	US Bureau of Labor Statistics	European Commission, DG EMPL	Nesta (Private company)	SkillsFuture Singapore	National Skills Commission	Employment and Social Development Canada
Granularity	1016 occupations, 177 elements covering skills, knowledge, abilities, work activities and work styles, and around 18,000 tasks	3008 occupations, 13,890 skills/competence, knowledge	41 million adverts, 10,500 skills	1,692 occupations, 10,000 skills (Critical core skills, Technical skills and competencies)	857 occupations, 10 core competencies, 2,136 specialist tasks and 70 technology tools	900 occupations, around 250 elements covering skills, abilities, attributes, knowledge, interests, work context, work activities and tools and technologies.

Structure	6 domains (occupation-specific information, occupational requirements, workforce characteristics, experience requirements, worker requirements, worker characteristics)	3 pillars (occupations, skills/competence, qualifications)	4 layers (Broad clusters, skills groups, skills clusters, and unique skills)	5 layers (Level 1-4 clusters, branching out to "unique skills")	3 layers (Cluster family, Cluster, task)	8 domains (Skills, Abilities, Personal attributes, Knowledge, Interests, Work context, Work activities, Tools and technologies)
Skills "importance" rating **(i.e. How important a skill is for an occupation)**	Scale of 1-5	Binary (Essential / Optional)	% in job adverts	Ranking of top 5 critical core skills	N/A	Currently being explored
Skills "level" rating **(i.e. What level of skill is required for an occupation)**	Level (1-7)	N/A	N/A	Technical skills and competencies (Proficiency Level 1-6) Critical core skills (Basic, Intermediate, Advanced)	Scale of 1-10 and respective 3 levels (Basic 1—3, Intermediate 4-6 and High 8-9)	Currently being explored
Link with qualifications	No direct link	Yes (to rely on Europass for information at the EU level, pilot project in 2019 of linking learning outcomes of qualifications with skills)	No direct link	Yes in terms of levels (Technical skill levels correspond to Singaporean qualification levels)	No direct link	No direct link
Data dissemination	Website (Interactive interface, Excel format, API)	Website (Hierarchical structure, API)	Website (Interactive interface)	Website (Interactive interface) By industry, sector information, career pathways, occupation and job roles, existing and emerging skills, training programmes for skills upgrading and mastery	Website (Interactive interface, Excel format)	Forthcoming Website (Interactive interface)
Updates	Regularly	Regularly	Ad-hoc	Regularly	Regularly	N/A
Cost implications	High	High	Low	High	High	High

*Sources: Authors' compilation based on Australian Bureau of Statistics (2022), Djumalieva and Sleeman (2018), European Commission (2022), Government of Canada (2022), National Center for O*NET Development (2019, 2022), National Skills Commission (2022), Popov et al. (2022).*

Each taxonomy comes with its own strengths and weaknesses, in terms of its ability to address specific policy questions, representativeness in data and ease of regular updates, among other aspects. The ability of taxonomies to address policy questions depends, at least partially, on its hierarchical structure and skills categorization. For instance, if a taxonomy provides data on skills, abilities, knowledge and tasks at a very detailed level, but without layer(s) of more aggregated clusters or groups (e.g., ESCO), such taxonomy would certainly be useful for identifying very specific skills gaps, but less suitable for analysing trends. Similarly, if a taxonomy has many detailed categories for technical skills but a small number of categories for transversal skills (e.g., SST), or even completely excludes transversal skills (e.g., the UK Skills Taxonomy), the ability of such taxonomy to give insights into transitions between occupations would be predominantly based on technical skills and thus could be compromised. Lastly, there is a trade-off between the representativeness of data and the ease of updates. A "hybrid" approach to data collection, combining the quantitative data from online job adverts and qualitative validation by experts (e.g., ESCO), would ensure quality of data, but may be costly to update. The taxonomy that solely depends on online job adverts (e.g., the UK skills Taxonomy) would be relatively easy to update but with a risk of bias in its coverage in term of population groups, sectors, skills requirements, skill levels, among other aspects.

3.2.2 Towards a global taxonomy

To enable G20 countries to communicate with one another using a common language with respect to skills, there is an urgent need to develop a global skills taxonomy, broad enough to be applied to the realities across different countries and yet detailed enough to capture skills and competencies needs. The development of a global taxonomy requires a substantial amount of time and resources. In recent years, however, the advent of highly capable new technologies such as machine learning and natural language processing and the exponential growth of data have significantly lowered these barriers to entry. As a result, there has been a few attempts among national and regional taxonomies in G20 countries to come up with a more unified framework, through the development of "crosswalks– i.e., the adaptation of a national taxonomy in another country – and the construction of joint conceptual frameworks. There is also an attempt in the research community to develop a global skill taxonomy for research purposes.

A case in point is **the crosswalk between O*NET and ESCO** developed with a view to supporting interoperability between the two taxonomies. Its development uses natural language processing model that matches O*NET occupations to ESCO occupations based on semantic similarity, further validated by the experts. As a result, all the ESCO occupations are mapped to O*NET occupations, in the "O*NET-ESCO Crosswalk table". The output can be downloaded and utilised to support job-matching platforms, research and analysis as well as to inform upskilling and reskilling policies and job matching by providing insights for the US and EU labour markets.

Adaptation of O*NET for a national taxonomy in another country is also widely observed. Indonesia's Occupational Tasks and Skills (Indotask) adapts skills and tasks modules of the O*NET. The skills module was replicated, due to its complementarity to the on-going efforts in Indonesia to describe skills using online real-time data on job postings. The pilot collected information on 394 unique tasks statements from the Indonesia's national occupational classification (KBJI) manual. A wide range of insights have emerged through the pilot implementation. These include the finding about the relative importance of basic skills (such as speaking, reading comprehension, and active listening) in the Indonesian context. Large differences in the importance of certain skills between O*NET and Indonesia were also found, especially in semi-skilled occupations. A few methodological lessons were learnt, including the number of responses that can be overwhelming, and the difficulties in the online survey responses due to the lack of digital literacy among the respondents (World Bank Group, et al, 2020). Adaptation of O*NET can be observed in other G20 countries, such as Australia, Canada, Germany and Italy.

The O*NET has also been adapted by countries outside the G20. The O*NET Uruguay Project, by the World Bank and the Ministry of Labour and Social Security (MTSS), implemented a survey following the O*NET model to characterize 23 selected occupations. An algorithm was used to generate a map of occupations included the skills, knowledge, and experience required for each job. The Uruguay project adapted the O*NET elements with some adjustment to descriptors, while maintaining the O*NET's Content Model structure. The adjustments included modifying "tasks" descriptions. The data collection was conducted through an online questionnaire to the incumbent workers and enterprises. Data are used for career counselling and training (González, 2021).

The ILO also used the case of Uruguay and piloted **a global skills taxonomy** that is comprehensive and succinct and can be applied to individual country context (Bennett et al. 2022). The skills taxonomy was piloted using online data from the Uruguayan online job board "BuscoJobs". The taxonomy consists of 3 broad categories: cognitive, socioemotional, and manual skills, and 14 more detailed sub-categories defined in terms of keywords and expressions. This taxonomy extended the approach of Deming and Kahn (2018), by adding information from a range of different studies and O*NET Uruguay and a category of manual skills. The taxonomy aims to be flexible and adaptable to middle- and low-income countries.

3.3 Internationally comparable indicators and their potential use in G20 countries

The potential G20 skills gaps portal proposed by the Indian Presidency and to be discussed at the EWG meeting can be composed of two sets of indicators: the basic set as a minimum data requirement across G20 countries (see 3.3.1), and an extended set of indicators that might not be available across G20 countries at present or may be collected in some of G20 countries but not in a comparable manner (see 3.3.2)

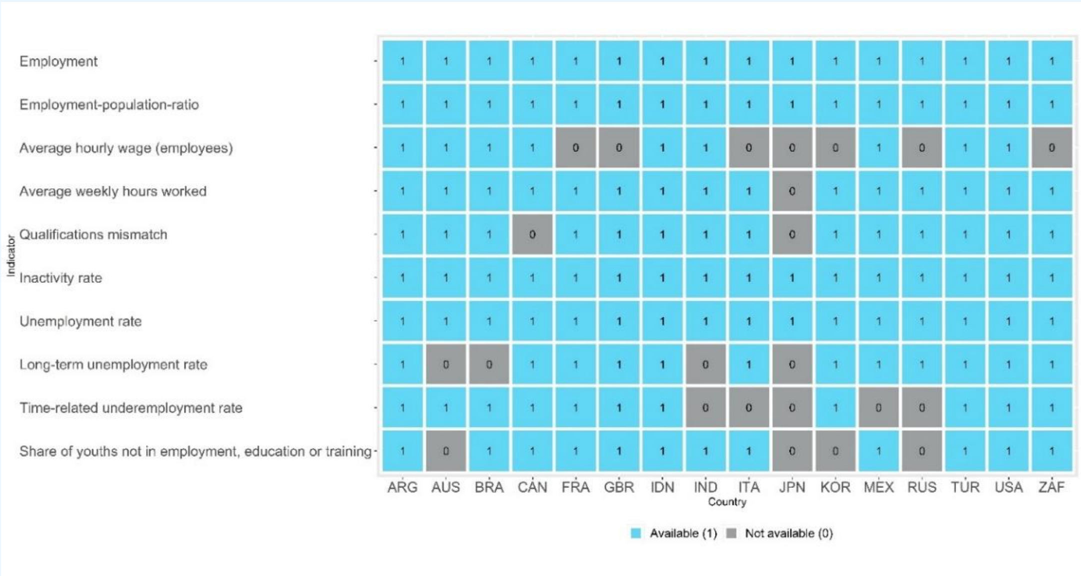
3.3.1 The basic set of indicators

Annex A Table 1 includes a list of basic indicators that represent a minimum requirement to measure skills supply, demand, and mismatch. Due to the relative difficulty in observing and measuring the actual skills that workers possess, proxy indicators derived from labour force surveys will be discussed. Aside from being widely available, the usage of data from labour force surveys has the benefit of being statistically representative of the population and could achieve international comparability when processed based on international standards and guidelines (e.g., ILO Harmonized Microdata collection). Some of these indicators are of a contextual nature, while others measure different types of skills mismatches or add the measurement elements for the in-depth analysis of mismatch such as the wage dynamics by occupation.

Assessment of the availability of indicators across G20 countries based on data from labour force surveys shared and processed by the ILO

The analysis below leverages on the ILO Harmonized Microdata collection which is systematically processed by the Statistics department of the ILO (ILOSTAT) to generate comparable indicators based on international standards.

▶ Figure 1. Data availability by indicator, by country



Note: Data for CHN, DEU and SAU are not available. Data refers to 2021 except for AUS, IND (2020) and GBR, JPN (2019). Data availability by indicator depends solely on whether the country shares the variables with ILOSTAT. A country may have the required variables collected through labour force surveys to construct the indicator.

Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

Even for this basic set of indicators, some crucial gaps exist. As **Figure 1** shows, the lack of available data on wages of employees is the most severe gap followed by data on the time-related underemployment rate, the long-term unemployment rate, the share of youth not in employment, education or training (NEET rate), qualifications mismatch (due to lack of data on occupations or the highest qualifications attained) and weekly hours worked. The availability of these statistics plays an essential role in the development, monitoring and evaluation of employment, education, and migration policies. For instance, the lack of occupation level data hampers a more detailed and nuanced understanding of the vastly different labour market situation across occupations. Also, the computation of the share of workers who are over/underqualified, a useful approximation of existing skills mismatches, would not be possible. In all countries, it is important to kick-start an exchange on how this data can be collected and shared as well as peer learning to foster capacity building and collaboration.

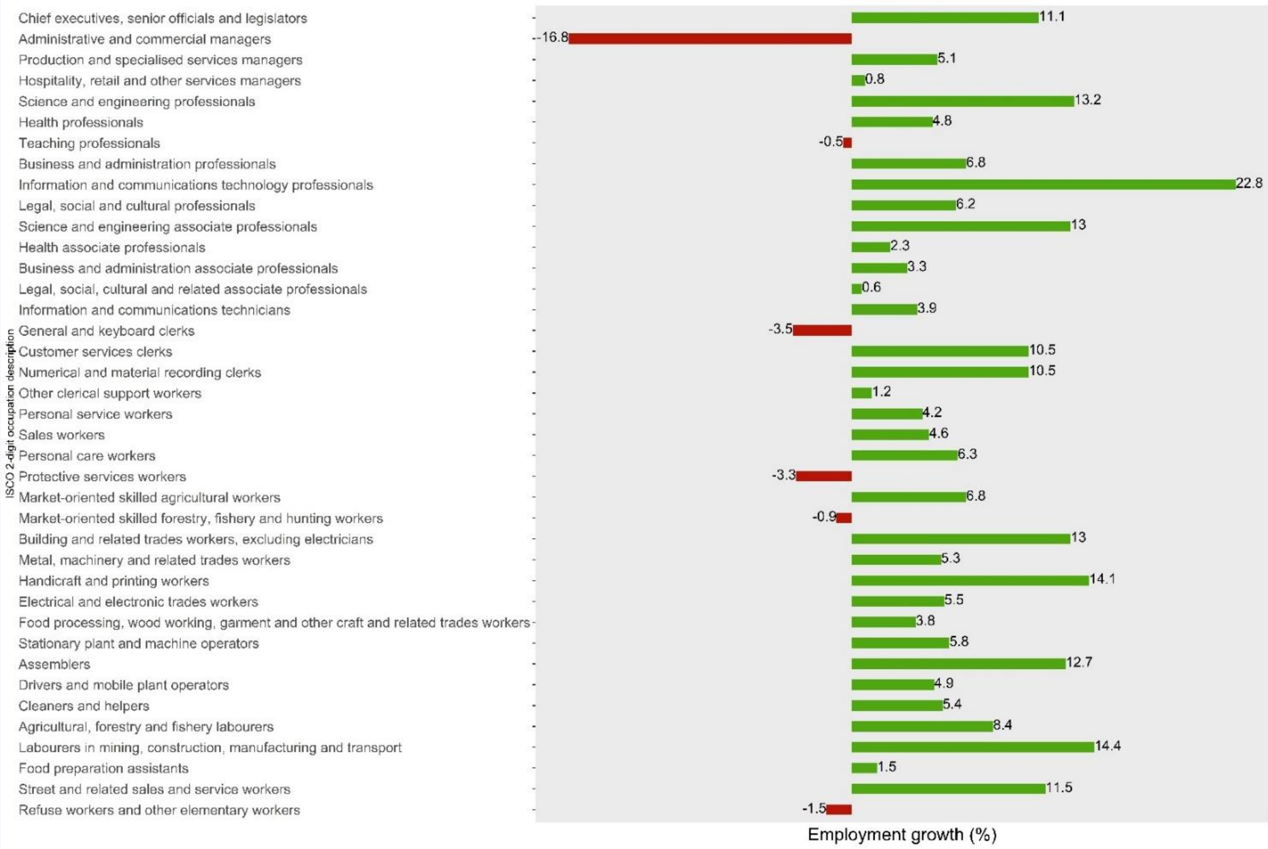
Selected skills demand and supply indicators: Demonstration of potential use

A brief demonstration of how some of these basic indicators could be used to analyse the changes in skills demand and supply is presented below. Contextual indicators such as the employment to population ratio, the unemployment rate and the labour force participation rate do not directly suggest mismatches of skill needs but could be used to understand the context in which skills supply and demand meet (see **Annex B**).

Employment growth by occupation

An increase in the quantity of employed workers in the economy can be interpreted as an indication that demand is rising or decreasing for certain occupations, which could generate shortages or surpluses for workers with related skill sets.

▶ Figure 2. Employment growth by ISCO-2digits occupation group: Brazil

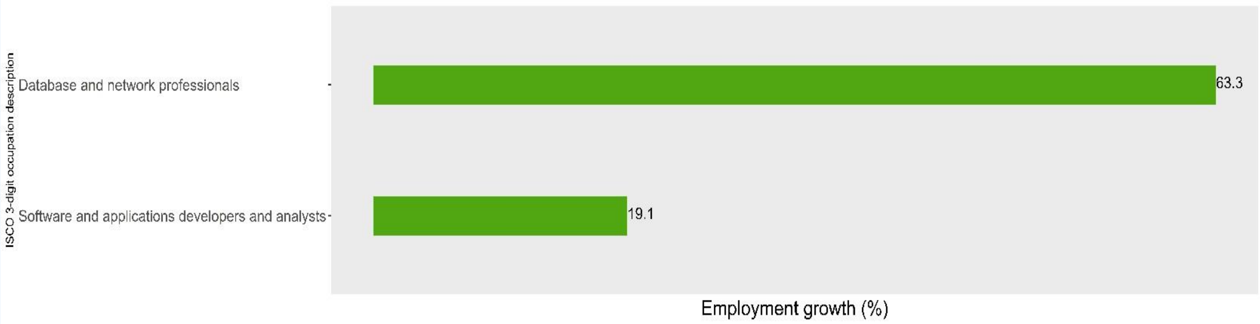


Note: For all occupation groups, employment growth refers to the difference of employment levels between 2021 and 2020.

Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

As illustrated in **Figure 2**, In Brazil, among persons in employment, information and communications technology (ICT) professionals saw the greatest year-on-year employment growth of +22.8%. However, to understand what occupations and skills were most in demand, it is necessary to use a more granular level of the indicator.

▶ **Figure 3. Employment growth by ISCO-3digits for ICT professionals: Brazil**



Note: For all occupation groups, employment growth refers to the difference of employment levels between 2021 and 2020.

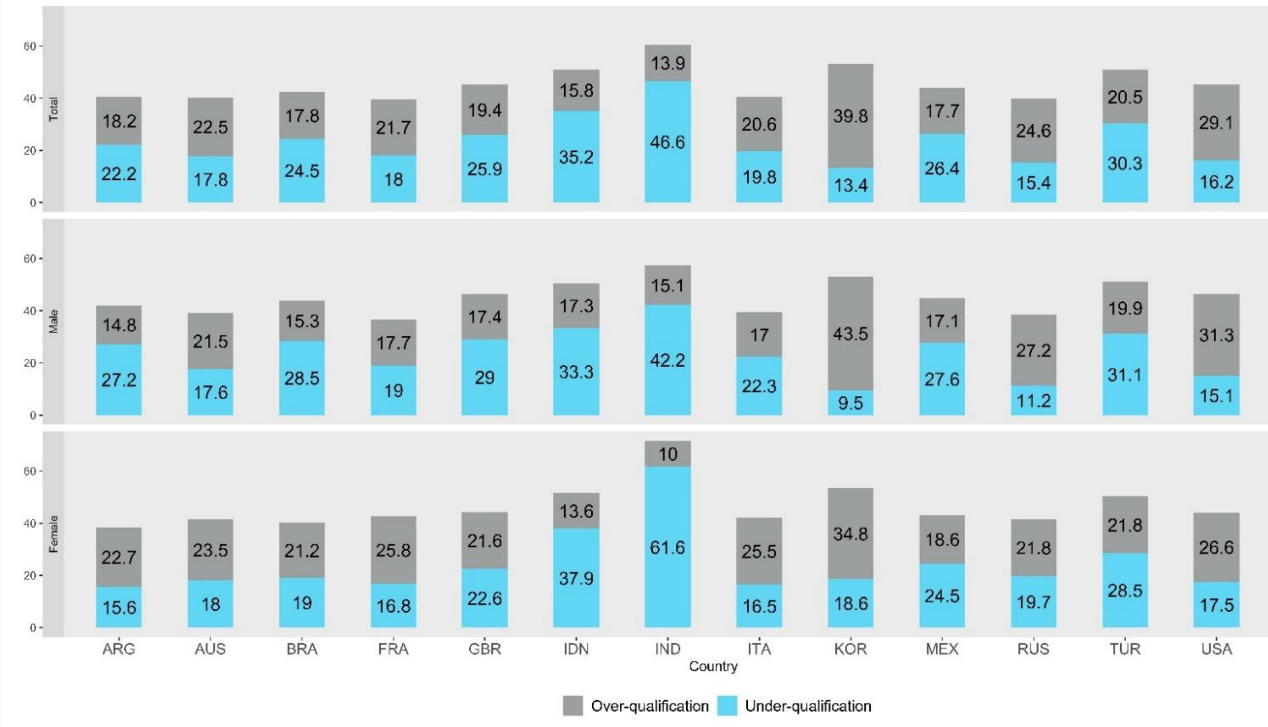
Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

As seen from **Figure 3**, even though ICT jobs experienced growth, there has been a large variation in the growth rate across occupations. The growth in demand for database and network professionals (i.e. computer and network professionals, database designers and administrators and system administrators) is more than 3 times that of software and applications developers and analysts (i.e., web and multimedia developers, software developers, systems analysts and applications programmers). This could largely be driven by the greater demand for ICT infrastructure due to the massive shift to teleworking and online learning in the context of the COVID-19 pandemic as employers utilised digital technologies to maintain operations. Among G20 countries with available data on occupations, details are mostly available only at ISCO-2digit level, rarely at ISCO-3 (United Kingdom, Italy) and ISCO-4digit levels (Brazil, France, South Africa). A more detailed level of granularity could potentially bring more accurate information about demand for skills, if the quality of data is observed.

Qualification mismatch

Qualification's mismatch refers to all persons in employment, whose level of qualification does not correspond to that required in their job.

▶ Figure 4. Proportion of overqualified and underqualified workers, by sex



Note: Data for CHN, DEU and SAU are not available. Data refer to individuals aged 15 and over. Data refer to 2021 for all countries except for AUS, ITA (2020) and GBR, IND (2019). The normative approach was used which is based on the educational requirements set out in ISCO for each ISCO-1D occupational group and on the level of education of each person in employment. A person is said to be over/underqualified or well-matched for the job if the level of education attained is higher/lower or equal to the ISCO educational requirements for their occupation. The normative approach has the advantage that workers in a given occupation and with a given level of education are consistently categorized.

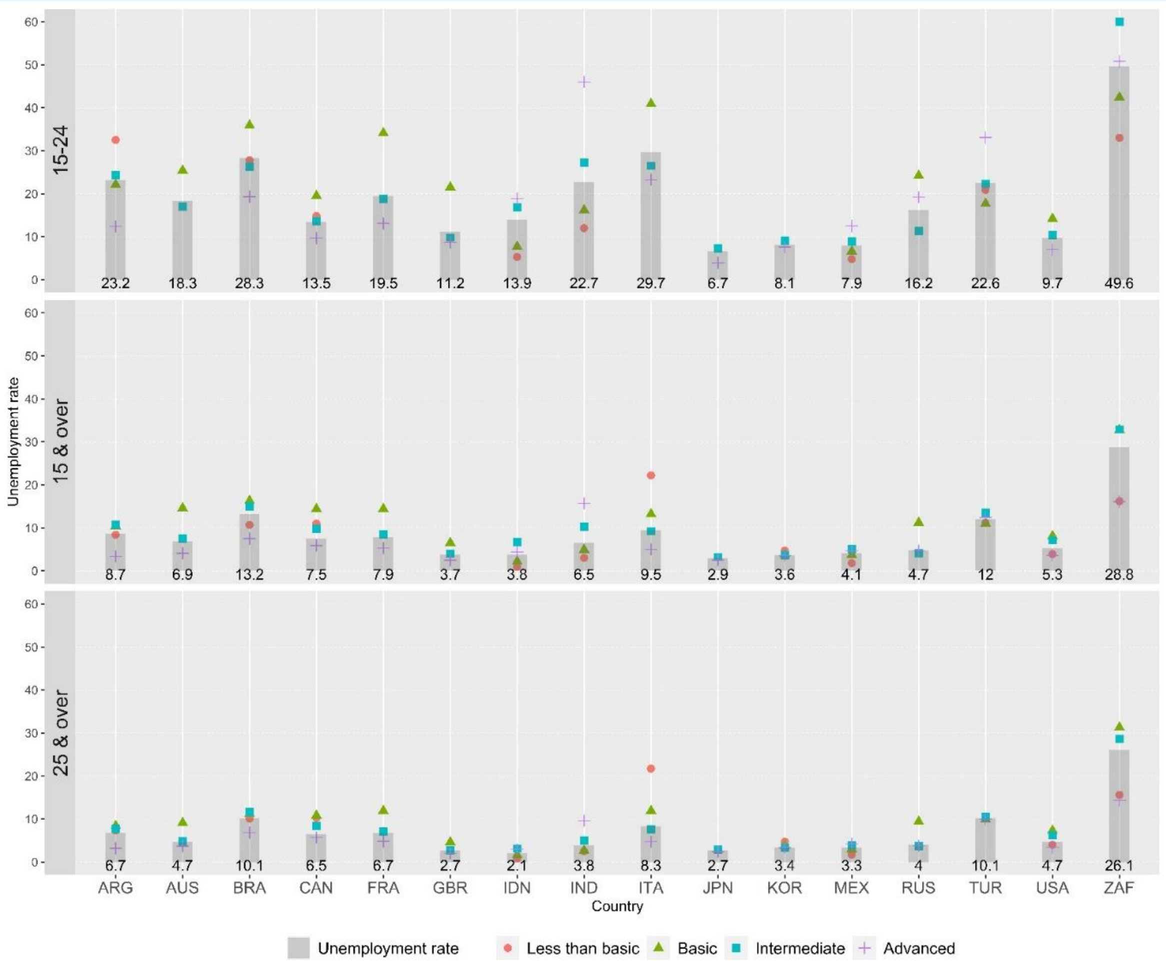
Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

Figure 4 shows that the issue of underqualification among persons in employment is more prevalent in G20 emerging economies – Argentina, Brazil, Indonesia, India, Mexico and Turkey. This is driven by a lower access to training and relatively lower levels of educational attainment in the populations. By contrast, overqualification is more prevalent in G20 advanced economies. Taking a simple average across G20 countries with available data, close to half (46%) had levels of educational attainment that did not match that required by their jobs, with 23.6% who were underqualified and 22.4% who were overqualified. The mismatch is the highest for India (60.5%) followed by Korea (53.2%), Indonesia (51%), Turkey (50.8%) and South Africa (50.5%). In India, nearly every second worker is in jobs requiring higher levels of education with underqualification especially affecting female workers. On the contrary, in Korea, close to 40% are working in jobs below their level of education, especially male workers, an outcome likely due to a highly educated population and not enough jobs available at higher skill levels.

Disaggregation by sex shows higher incidence of overqualification among women and higher incidence of under-qualification among men in majority of G20 countries with available data. High rates of overqualification may reflect the overall inefficiency of the decent work creation opportunities, as skilled workers remain employed in jobs that do not exploit their fullest potential. The issue of underqualification highlights the low relevance in education and training, emphasizing the need to modernize curricula. Improving systems of skill needs anticipation is necessary to facilitate matching between demand and supply and reduce both over- and underqualification.

Unemployment rate and NEET rate by broad levels of educational attainment

▶ Figure 5. Unemployment rate by age group, by broad level of educational attainment, by country



Note: Data for CHN, DEU and SAU are not available. Data refer to 2021 for all countries with the exception of AUS, JPN (2020) and GBR, IND (2019). Some data are hidden due to sample size constraints (sample size is less than 15), affecting statistical reliability.

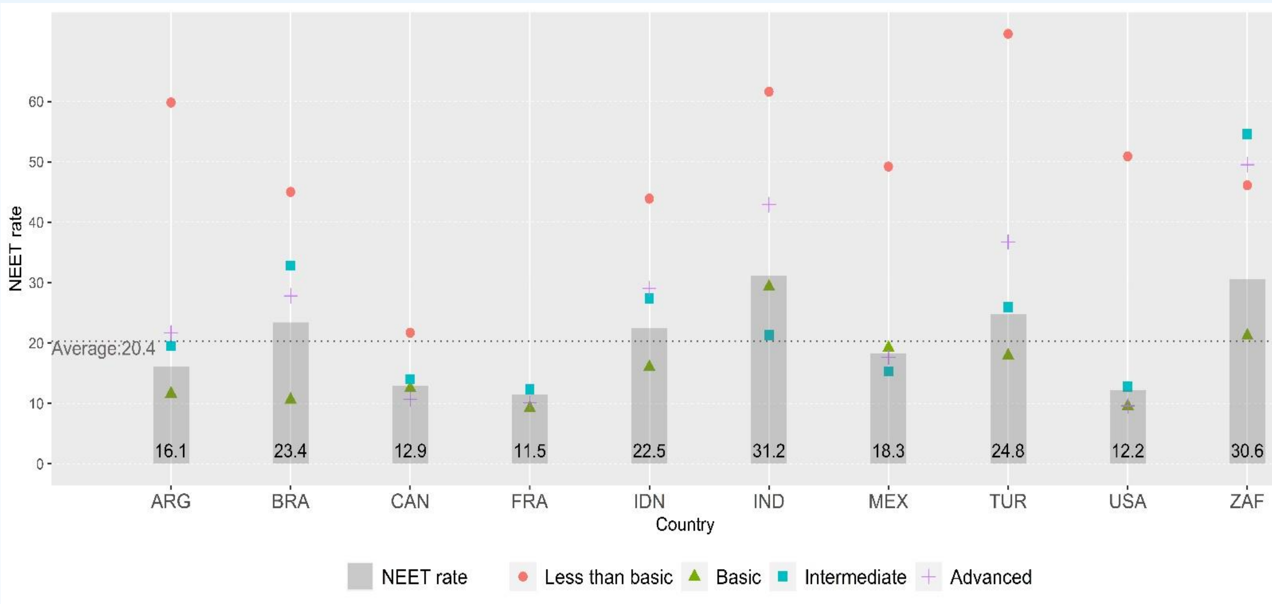
Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

Figure 5 shows that the unemployment rate is significantly higher for youths (15-24) across all broad levels of educational attainment as compared to the adult working-age population (25 and over). For individuals aged 15 and over, taking a simple average across G20 countries, the unemployment rate is 8.6% among individuals with less than basic education, 11.2% for those with basic education, 9.5% for those with intermediate level of education and 6.3% for those with tertiary education.

Among youths (15-24), for majority of countries, the unemployment rate decreases with increasing level of educational attainment, except for G20 emerging economies Indonesia, India, Mexico, Turkey and South Africa where young people with higher levels of educational attainments experience higher unemployment rates. The highest unemployment and NEET rates of youths with tertiary qualifications is found in South Africa where 1 in 2 highly educated youths were unemployed (**Figure 5**), and neither in employment nor in education or training (**Figure 6**). Such mismatch may result from the insufficient quality and relevance of education and training which are not adapted to the needs of employers.

Among individuals aged 15 and over, the pursuit of higher levels of educational attainment increases the likelihood of employment by a large extent in Australia where the unemployment rate of individuals with a basic education (14.6%) is more than 3 times higher as compared to those with a tertiary education (4.1%) (**Figure 5**). High levels of unemployment among individuals with lower levels of educational attainments is problematic. In Italy, the unemployment rate of 22.2% among individuals with less than basic levels of educational attainment is 11 percentage-points higher than the G20 average among countries with available data. This could be attributed to the lack of demand for skills possessed by those with basic level of education and point to the urgent need for upskilling measures.

▶ Figure 6. NEET rate by broad level of educational attainment, by country



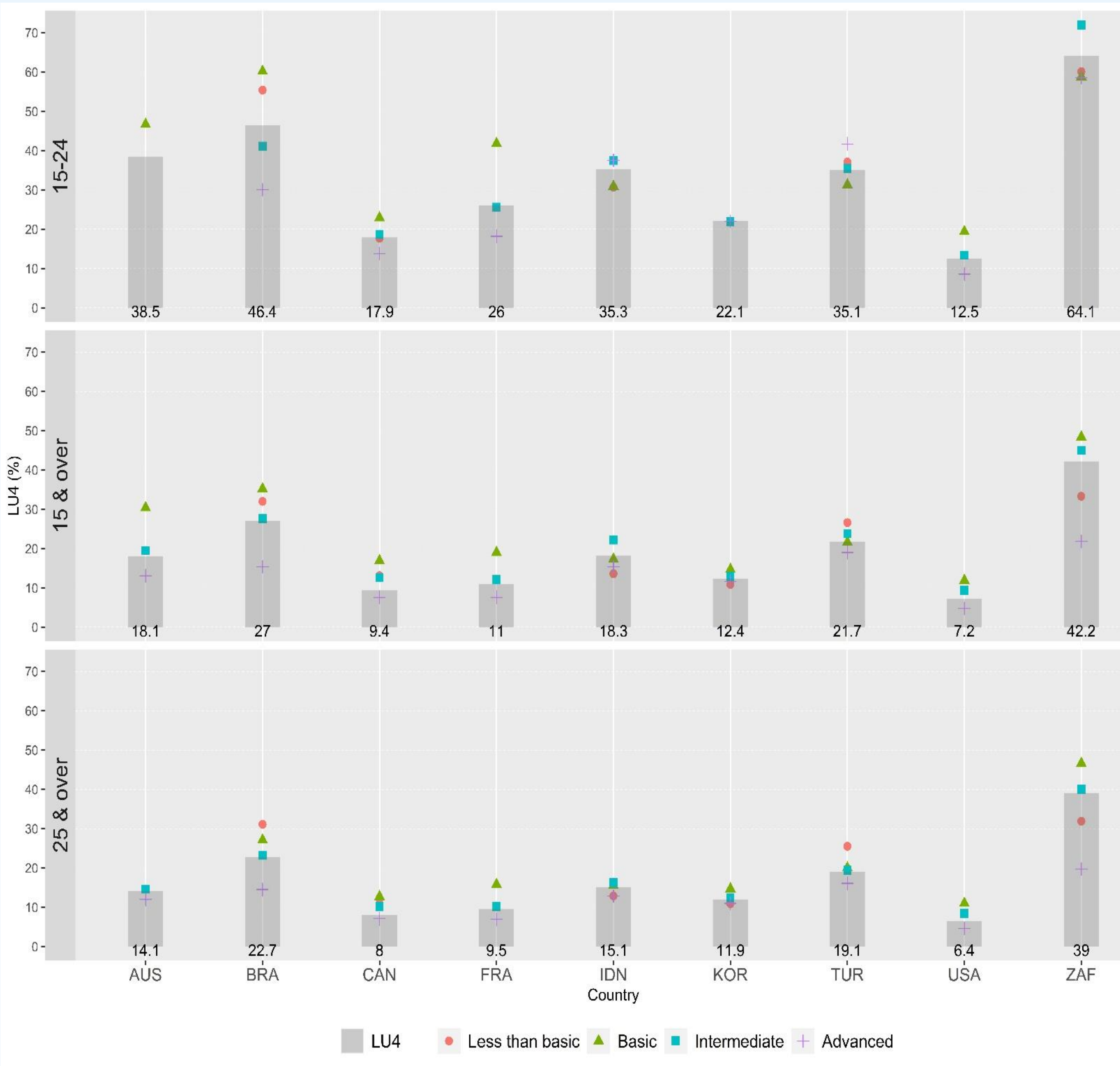
Note: Data refers to youths aged 15-24. Data not available for AUS, CHN, DEU, GBR, ITA, JPN, KOR, RUS and SAU. Data refer to 2021 for all countries with the exception of IND (2019). Some data are hidden due to sample size constraints (sample size is less than 15), affecting statistical reliability.

Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

Composite rate of labour underutilization

The indicators reported in **Figure 1** could be combined to form the rate of labour underutilization (19th ICLS, 2013). The indicator would identify persons with unmet needs for income-generating work due to mismatches between labour supply and demand (i.e., labour slack, low earnings, skills mismatch), reflecting the insufficient labour absorption. It is computed as the sum of employed persons whose hours of work are insufficient in relation to the hours they are willing and available to engage (i.e. time-related underemployment), the unemployed as well as the potential labour force comprising of inactive persons who are either seeking but not available to work (i.e. unavailable job seekers) or those who are not seeking and available to work (i.e. available potential job seekers). In addition to the unemployment rate discussed above, labour underutilization enriches the analysis of the efficiency and productive potential of the labour market.

▶ Figure 7. Measure of labour underutilization (LU4) by broad level of educational attainment, by country



Note: Data not available for ARG, GBR, ITA, JPN, RUS, IND and MEX. Data refers to 2021 for all countries with the exception of AUS (2020). Some data are hidden due to sample size constraints (sample size is less than 15), affecting statistical reliability.

Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

Figure 7 shows that across all age groups, the labour underutilization rate ranges from being 1.2 times to 7.2 times higher than the unemployment rate (**Figure 5**). The greatest difference between these measures is found in Indonesia among individuals aged 25 and over, including for those with tertiary level of education. This suggests that despite having an unemployment rate (2.1%) that is well below the average (6.6%) of G20 countries with available data, Indonesia has a relatively high rate of labour underutilization (15.1%), just slightly below the average of 16.2% for G20 countries with available data. The highest labour underutilization rate of 64.1% is found in South Africa among youths (15-24), including educated youth, pointing to the unmet need for jobs and limited access to the labour market.

Composite indicator of skills shortages and surpluses

The OECD[1] and ILO Skills for Jobs[2] databases and respective portals provide internationally comparable measures of skills shortages and surpluses through the construction of a composite indicator, arriving at a multidimensional picture of the surplus and shortage of workers in occupations which is mapped to the underlying skills requirements. Together, the datasets cover 66 countries, ranging from developed to middle-income economies. The data indicate which skills are in shortage (hard-to-find) or surplus (easy-to-find) in each country. The indicator measuring skills shortages and surpluses is constructed following a two-step approach.

In the first step, an "occupational imbalance indicator" is a composite indicator of occupational imbalance that is calculated for occupation groups at the 2-digit ISCO-08 level. This calculation is based on labour market information from household surveys and consists of five sub-indicators: i) wage growth, ii) employment growth, iii) hours worked growth, iv) change in unemployment rate, and v) change in underqualification rate. For every country, occupational group and sub-indicator, long-run trends are compared to the economy-wide trend. This standardisation sheds light on whether the specific occupational group is outperforming/underperforming the rest. When combining the standardised sub-indicator into the composite occupational imbalance indicator, each sub-indicator is weighted equally, except for employment growth, which is half the weight of others.

In the second step, the composite occupational imbalance indicator is linked to a mapping of skill requirements by occupation. By aggregating the data by skill, using the number of employed persons by occupation as a weight, a skill imbalance indicator is obtained for each country and skill dimension.

The ILO Skills for Jobs database extends the methodological approach above to low-and-middle income countries. A challenge in doing so involved the greater number of missing data observations for each sub-indicator requiring imputation, where greater scrutiny on its implication in introducing unwanted biasness was required.

3.3.2 Extended set of indicators

A number of additional indicators (see **Annex A, Table 2**) can help assess the extent to which the qualifications and/or skills of persons in employment correspond to the requirements by their jobs. They consist of an individual's self-perceived match between his/her level and type of skills and the skills required by the job, employer's assessment of hard-to-find skills and hard-to-fill vacancies, assessment of the quality and relevance of current education and training programmes, and indicators that reflect hiring behaviour of firms.

While the core set of indicators measures skill mismatches through labour market signals, skill supply and demand can also be assessed through the direct measurement of the skills and competencies of individuals and the skill challenges faced by employers. Establishment skills surveys provide direct information on skill gaps and needs in the world of work, and as such are very useful. However, the results of the surveys should be interpreted with caution as they may represent a one-sided perspective by employers, not being representative of the economy or sector, and are hard to implement in the situation of high shares of the informal economy. It is advisable to use the results as qualitative rather than quantitative measures and, for a more balanced interpretation, to combine with the surveys among workers.

[1] https://www.oecdskillsforjobsdatabase.org

[2] https://www.ilo.org/ilostat-files/Documents/skillsforjobs.html

The ILO, OECD, World Bank and Cedefop run dedicated household and employer surveys to collect skills gaps and needs information. Additionally, the ManpowerGroup, conducts the Employment Outlook survey (EOS) and Talent Shortage Survey (TSS) of employers. **Figure 8** summarises the availability of data across G20 countries.

▶ Figure 8. Data availability across survey sources by country

Note: Data for STEP refers to the Yunnan Province for CHN. See Annex A, Table 3 for more information.

The Survey of Adult Skills as part of its Programme for the International Assessment of Adult Competencies (PIAAC) by the OECD is the household survey which assesses the level of intensity and frequency of skill use at work and in everyday life along several skill dimensions: cognitive and socio-emotional, interaction and social skills, physical skills and learning skills. The OECD is working on an employer survey including a set of questions on skill gaps.

The Skills Towards Employability and Productivity Programme (STEP) survey by the World Bank focuses on low and middle-income countries. Its household and employer surveys ask respondents to report on the intensity and complexity of use of cognitive skills[3] and job-relevant skills[4] . The common direct assessment module used in PIAAC and STEP evaluates the skills of adults in three fundamental domains through a range of literacy, numeracy, problem solving in technology rich environments and adaptive problem-solving tasks with varying difficulties.

The School-to-Work Transition Survey (SWTS) by the ILO follows the situation of young people (15-29) on the labour market and asks them to self-evaluate their skills and report on mismatch aspects. Employer survey asks employers to rate the general aptitude level of job applicants for writing, technical and oral communication skills. In addition, for collecting information about type and level of skills available by workers and skills required by their jobs, the ILO has developed a module that could be attached to the ongoing LFS surveys.

The European Skills and Jobs survey (ESJS) by Cedefop ask respondents to self-assess the level and importance of cognitive, digital, transversal and technical/job specific skills[5] required to do their current job, a comparison against their own skills, and to assess their self-perceived degree of skills mismatch.

[3] List of skills assessed (reading, writing, numeracy)

[4] List of skills assessed (interpersonal skills, use of technology, job-specific skills, language, autonomy, problem solving and learning)

[5] List of skills assessed (literacy, numeracy, ICT, technical skills, communication skills, teamwork skills, foreign language skills, customer handling skills, problem solving, learning skills, planning and organisation skills)

The EOS/TSS ManpowerGroup employer surveys ask employers for details on hard-to-fill vacancies, occupations in demand, ranking soft skills and occupations by hiring intentions.

At the country level, the Department for Education (DfE) of the United Kingdom with the assistance of its research partners has been conducting an employer skills survey biennially since 2011 with latest results available for 2019. The survey collects information on hard-to-fill vacancies related to skills shortages and on skills gaps by occupation. In Canada, Statistics Canada in partnership with Employment and Social Development Canada (ESDC) runs the Survey of Employers on Workers' Skills (SEWS), collects information on the top 3 most difficult-to-find skills among job candidates as well as the skills gaps (proficiency and skills in need of improvement) of the current firm's workforce.

Potential of analysing real-time big data on online job vacancies and job applicants for G20

The 2018 report to the G20 Employment Working Group (ILO-OECD 2018) discussed how the rapid pace of technological innovation makes it challenging to anticipate skills needs. Big real-time data may be a solution to gather more timely skill needs information. Some G20 countries have started to explore and already been implementing the use of big data to improve skills anticipation and matching capabilities. Examples of this include the pan-European real-time job vacancy tool developed by Cedefop, and the job market analysis offered by Lightcast (the former Emsi and Burning Glass Technologies) that cover mostly Anglo-Saxon and European countries.

Big data have the potential to complement existing survey-based skills intelligence, uncovering skill trends by occupations and sectors at a very granular level, on both skills supply (e.g., online CVs, worker profiles, education and training programme curricula) and demand (e.g. employer job advertisements). The representativeness of big data depends on the availability of a well-developed digital infrastructure, digital literacy of the population as well as the digital readiness and level of engagement by various stakeholders. There may be biases linked to representativeness, especially in the countries with large share of informal economies. There are also limitations and concerns related to privacy and legal considerations (ILO, 2020; Cedefop et al., 2021.).

The collection and cleaning of data from job postings and resumes involves considerable effort and is highly technical, involving web scraping and crawling, natural language processing (NLP) and machine/deep learning techniques. Adding onto the complexity involves the extraction, organization, standardization, and categorization of skills into a consistent and coherent format.

There are good examples of the big data usage as a complementary source to existing labour market and skills intelligence to develop value-added policies and strategies. For instance, the Migration Advisory Committee in the United Kingdom uses information gathered from online job vacancies and labour market surveys to develop nine data driven indicators of labour market conditions to assess which occupations are in shortage. In Korea, the employment information platform (Work-Net) which integrates data from 31 public and private job search websites, operated by the Ministry of Employment and Labour and Korea Employment Information service uses AI powered job matching algorithms to recommend suitable jobs to job seekers.

3.4 Evidence-based policies and programmes to address skills gaps

Identifying the existence of a skills mismatch is an important first step towards determining the source and magnitude of the problem. Policy makers should rely on the use of both supply and demand side indicators (as discussed in section 3.3) along with complementary data sources (i.e. interviews with stakeholders, big data etc.) to design feasible and targeted policy interventions in the design and delivery of initial education and continuing training and labour market policies, subjecting potential solutions to rigorous debate and challenge. Monitoring and evaluation of the policy process follows through the tracking of results and outcomes.

It is crucial to ensure that information gathered is turned into action by presenting it in non-technical terms (e.g. packaging it into interactive visualisations) and disseminated through effective communication channels such as self-service labour market intelligence tools. For example, the Department of Employment and Workplace Relations in Australia developed Workforce Australia, an online tool which provides information on job search and matching for individuals, employment and service providers and businesses. It integrates data from online job portals, education and training institutions, employment service providers and offers a link to learning modules and work experience opportunities. The information is showcased in a manner that is user-friendly and intuitive.

3.5 Process and partners: Engagement of key stakeholders

Anticipating and building skills for future jobs and emerging sectors is essential in today's fast changing world. An important aspect of effective skills anticipation systems is to develop and support institutions and mechanisms to generate, collect, use, disseminate and develop evidence-based decisions. For skills anticipation and labour market intelligence to have an impact, it is necessary to involve all relevant stakeholders, each of them, playing an important role. Employers and their representatives ensure the transfer of direct demand-related labour market signals and can shape the design and delivery of training offer. The involvement of workers' representatives is key to highlight quality and social inclusiveness in skills anticipation and intelligence as they invariably bring important insights to the benefits of all in the process. Governments facilitate the data collection on specific target groups, including disadvantaged groups, making sure that the process is inclusive. Governments' role is also very important in supporting coordination of data collection and analysis, ensuring the complementarity of data and preventing data gaps and overlaps in data collection. A whole-of-government approach also supports coordination across policy areas, including industrial polices, and the collection and analysis of data on relevant impact on skill demand. Education and training providers and institutions in charge of curricula and qualifications are key players in adapting the learning offer and ensuring its quality in line with labour market demand. Coordination and stakeholders' engagement can be supported by institutional development building and capacitating tripartite skills platforms at national and sectoral levels.

▶ Questions for discussion

- What common sets of **indicators** can be used to make the skills gaps assessments comparable across countries and obtain a global picture? Are these available for all G20 countries? How can better data availability be facilitated?
- What common **taxonomies** can be used to make the skills gaps assessments comparable across countries and obtain a global picture?
- How can G20 facilitate better data on current and future skills gaps? What can be done to ensure better comparability of data across countries?
- Does the framework for the G20 skills gaps mapping and the related data portal correspond to the needs of G0 member states? Is the proposed set of indicators for the portal relevant? What will be specific steps in the roadmap to populating and maintaining the G20 portal?

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▶ Annex A

▶ Table 1: Basic set of indicators

Indicator	Description/Definition	Formula	Implications on skills gaps
Employment-to-population ratio	Employment-to-population ratio is defined as the proportion of a country's working-age population that is employed.	$\frac{Number\ of\ persons\ in\ employment}{Number\ of\ persons\ in\ working-age\ population} \times 100\%$	Analysis on employment-to-population ratio provides an indication of the relative demand for skills.

Employment (% change YoY)	According to the 13th International Conference of Labour Statisticians (ICLS), employment comprises all persons of working age who during a specified brief period, such as one week or one day, were in the following categories: a) paid employment (whether at work or with a job but not at work); or b) self-employment (whether at work or with an enterprise but not at work).	$\frac{Persons\ in\ employment_{Year\ X} - Persons\ in\ employment_{Year\ (X-1)}}{Persons\ in\ employment_{Year\ (X-1)}} \times 100\%$	A positive change in employment signals an increase in demand, possibly indicating the pre-condition under which skills shortages are likely to occur. A negative change in employment signals A decrease in demand, possibly indicating the pre-condition under which skills surpluses are likely to occur.

Average hourly wage (% change YoY)	The earnings of employees relate to the gross remuneration (i.e the total before any deductions are made by the employer in respect of taxes, contributions of employees to social security and pension schemes, life insurance premiums, union dues and other obligations of employees) in cash and in kind paid to employees, as a rule at regular intervals, for time worked or work done together with remuneration for time not worked, such as annual vacation, other type of paid leave or holidays. Earnings exclude employers' contributions in respect of their employees paid to social security and pension schemes and also the benefits received by employees under these schemes. Earnings also exclude severance and termination pay.	$\text{Hourly wage} = \frac{Monthly\ income \times 12\ (number\ of\ months\ in\ a\ year)}{Weekly\ hours\ worked \times 52\ (number\ of\ weeks\ in\ a\ year)}$ $\frac{Average\ hourly\ wage_{Year\ X} - Average\ hourly\ wage_{Year\ (X-1)}}{Average\ hourly\ wage_{Year\ (X-1)}} \times 100\%$	An increase(decrease) in average hourly wage possibly reflects a relative difficulty(ease) of employers finding individuals with the right skills.

Average weekly hours worked (% change YoY)	The 19th ICLS promotes the collection of both usual and actual hours worked. 1. Hours usually worked relates to the typical value of hours actually worked in a job per a short reference period such as one week, over a long observation period of a month, quarter, season or year that comprises the short reference measurement period used. 2. Hours actually worked includes (a) "direct hours" or the time spent carrying out the tasks and duties of a job; (b) "related hours", or the time spent maintaining, facilitating or enhancing productive activities; (c) "down time", or time when a person in a job cannot work due to machinery or process breakdown, accident, lack of supplies or power or Internet access; and (d) "resting time", or time spent in short periods of rest.	$\frac{Total\ number\ of\ weekly\ hours\ worked\ by\ persons\ in\ employment}{Number\ of\ persons\ in\ employment}$ $\frac{Average\ weekly\ hours\ worked_{Year\ X} - Average\ weekly\ hours\ worked_{Year\ (X-1)}}{Average\ weekly\ hours\ worked_{Year\ (X-1)}} \times 100\%$	An increase (decrease) in average weekly hours worked possibly indicates that there exist skill shortages (surpluses).

Share of over/underqualified among persons in employment	Each individual is assigned a status (matched, overqualified, underqualified) depending on whether their level of education corresponds to the educational requirements for their particular occupation group. The approach used to identify mismatched workers is based on the educational requirements set out in the International Standard Classification of Occupations (ISCO) for each one-digit ISCO occupational group, and on the level of education of each person in employment (i.e a normative approach).	$\frac{Number\ of\ persons\ in\ employment\ who\ are\ over-qualified}{Number\ of\ persons\ in\ employment} \times 100\%$ $\frac{Number\ of\ persons\ in\ employment\ who\ are\ under-qualified}{Number\ of\ persons\ in\ employment} \times 100\%$	A higher(lower) share of individuals who are over/under-qualified reflects higher(lower) skills mismatch.

Unemployment rate for those previously employed	The unemployed are defined as comprising all persons above a specified age who during the reference period were "without work", "currently available for work", and "seeking work". The operational criteria for being classified as unemployed is stricter based on the standards adopted at the 19th ICLS where all three criteria a) being without a job, b) seeking a job, c) and being available must be met. The 13th ICLS standard was less strict and allowed countries to adjust the definition according to national circumstances (i.e two out of three criteria to be classified as unemployed). The measurement of unemployment is adopted in the 19th ICLS resolution concerning statistics of work, employment and labour underutilization.	$\frac{Number\ of\ persons\ who\ are\ unemployed}{Number\ of\ persons\ in\ the\ labour\ force} \times 100\%$	Provides indication on the relative difficulty for specific workers in re-entering the labour market, providing a proxy of the relative gaps between the skills demanded and supplied. High unemployment rates signal skill surpluses. Low unemployment rates signal shortages.

Long-term unemployment rate and share of long-term unemployed in total unemployment	Long-term unemployment looks at duration of unemployment (i.e. the length of time that an unemployed person has been without work, available for work and looking for work. The standard definition of long-term unemployment is all unemployed persons with continuous periods of unemployment extending for one year or longer (52 weeks and over). Long-term unemployment is measured in terms of a percentage of the overall labour force (long-term unemployment rate) and of total unemployment (incidence of long-term unemployment).	$\frac{Number\ of\ persons\ who\ are\ unemployed\ for\ one\ year\ or\ longer}{Number\ of\ persons\ in\ the\ labour\ force} \times 100\%$ $\frac{Number\ of\ persons\ who\ are\ unemployed\ for\ one\ year\ or\ longer}{Number\ of\ persons\ who\ are\ unemployed} \times 100\%$	A large proportion of long-term unemployed in labour force is likely to reflect structural problems in the labour market, including persisting skills mismatches. Analysis on persons in long-term unemployment by their level of education and previous occupation can shed light on persisting imbalances between skills supply and demand. High long-term unemployment rates among individuals with certain skills profiles signal a surplus of skills possessed by such individuals. Low long-term unemployment rates among individuals with certain skills profiles signal a shortage of skills possessed

			by such individuals.

Inactivity rate	Inactivity rate is the proportion of the working-age population that is not in the labour force. The labour force is defined as the sum of the employed and the unemployed. The remainder of the working-age population is the number of persons outside the labour force.	$\frac{Number\ of\ persons\ in\ outside\ the\ labour\ force}{Number\ of\ persons\ in\ working-age\ population} \times 100\%$	Individuals do not participate in the labour force for a variety of reasons, including skills mismatches. When skills mismatches are severe and long-lasting, one can be discouraged and fall out of the labour market. Analysis on persons who are inactive by level of education and previous occupation can shed light on potential imbalances between skills supply and demand. High inactivity rate among persons with certain skills profile could indicate a surplus of skills possessed by such individuals. Low inactivity rate among persons with certain skills

			profile could indicate a shortage of skills possessed by such individuals.

Time-related underemployment rate among persons in employment	Time-related underemployment relates to the number of employed persons whose hours of work in the reference period are insufficient in relation to a more desirable employment situation in which the person is willing and available to engage. Based on the 16th ICLS resolution, time-related underemployment includes all persons in employment who, during a short reference period, (a) wanted to work additional hours, (b) had worked less than a specified hours threshold (working time in all jobs), and (c) were available to work additional hours given an opportunity for more work.	$\frac{Number\ of\ persons\ in\ time-related\ underemployment}{Number\ of\ persons\ in\ employment} \times 100\%$	Time-related underemployment is an important aspect of labour underutilization, which can give an indication of skills underutilization. Skills underutilization can be caused by skills mismatches, among many other reasons. High time-related underemployment rates among persons with certain skills profiles signal surpluses of skill possessed by such individuals. Low time-related underemployment rates among persons with certain skills profiles signal shortages of skill possessed by such individuals.

Share of youth not in employment, education or training (NEET)	The percentage of the population of a given age group and sex who is not employed and not involved in further education or training.	$\frac{\text{Number of youth} - (\text{number of youth in employment} + \text{number of youth not in employment who are in eduction or training})}{\text{Number of youth}} \times 100\%$	High NEET rate among youth with certain skills profile could indicate a surplus of skills possessed by such individuals. Low NEET rate among youth with certain skills profile could indicate a shortage of skills possessed by such individuals.

Composite rate of labour underutilization (LU4) and new composite rate of skills underutilization (SU)	Labour underutilization is defined as all mismatches between labour supply and demand which translate into an unmet need for employment among the population. With the recognition of the limitations of the unemployment rate as the only measure of labour underutilization, current international recommendations on labour statistics uses additional labour underutilization measures. These include labour underutilization among employed persons "time-related underemployment", the unemployed, and identifies "potential labour force" among persons outside the labour force. Measures of labour underutilization: 1. Time-related underemployment (TRU) comprise all persons in employment, who satisfy the following three criteria during the reference period: a) are willing to work additional hours; b) are available to work additional hours i.e., are ready, within a specified	$LU4 = \frac{\text{Number in time–related underemployment} + \text{Number in unemployment} + \text{Number in potential labour force}}{\text{Number in labour force} + \text{Number in potential labour force}} \times 100\%$ $SU = \frac{\text{Number in time–related underemployment and overqualified} + \text{Number not in time–related underemployment and overqualified} + \text{Number in unemployment} + \text{Number in potential labour force}}{\text{Number in labour force} + \text{Number in potential labour force}} \times 100\%$	High composite rate of labour underutilization signal labour surpluses. High SU signals skills surpluses.

	subsequent period, to work additional hours, given opportunities for additional work; and c) worked less than a threshold relating to working time. 2. Unemployment persons not in employment, available and actively searching for a job. 3. Potential labour force (PLF) persons not in employment who express an interest in it but for whom existing conditions limit their active job search and/or their availability. Further categorised as Discouraged job seekers (not seeking, available) and Other PLF (seeking, not available).		

▶ Table 2: Extended list of indicators

The lists below are tentative and subject to further discussion and verification.

Skills Gaps Surveys to be directly asked to individuals (Supply side)

1. **Self-reported list of core skills[1] lacking to perform at current job, or the job one aspires** by status of employment, sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit)
2. **Self-reported list of technical skills lacking to perform at current job, or the job one aspires**, by status of employment, sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit)
3. **Degree[2] of match between the level of qualifications held and the level required for the job** by sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit)
4. **Degree of match between the level of skills held and the level and frequency of the skill required for the job** by sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit)
5. **Degree of match between the field of study held and that required for the job** by sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit)
6. **Engagement in skills development (**field and type of training/education**),** by sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit), level of education (ISCED 2011)
7. **Types of skills not in use** due to new technologies, work processes or products by sex, age, sector (ISIC Rev. 4 2-digit), occupation (ISCO-08 4 digit)

Skills Gaps Surveys to be directly asked to establishments (Demand side)

1. List of **hard-to-fill occupations** (ISCO-08 4-digit) due to lack of applicants with relevant skills and/or education and the **number of vacancies available**
2. List of **hard-to-find core skills**, by fresh graduate new entrants and overall workforce
3. List of **hard-to-find technical skills**, by fresh graduate new entrants and overall workforce
4. List of **occupations recruited** (ISCO-08 4-digit) and **number recruited**, within the reference period
5. List of **occupations laid off** (ISCO-08 4-digit) and **number laid off**, within the reference period
6. List of skill gaps (core and technical) among current employees
7. **Plan to implement new technologies, processes, products or services, and their relevant hiring/firing plans** within one year (Qualitative response)

▶ Table 3: Details of surveys by International Organizations

Surveys	Organization	Country (year)	Items captured (Individuals)	Items captured (Employers)
The Programme for the International Assessment of Adult Competencies (PIAAC)	OECD	Argentina (2017), Australia (2011-2012), Brazil (2015), Canada (2011-2012), China (2015), France (2011 -2012), Germany (2011-2012), India (2016-2017), Indonesia (2017), Italy (2011-2012), Japan (2011-2012), Mexico (2012), Russian Federation (2011-2012), Saudi Arabia (2016), South Africa (2015), South Korea (2012), Turkey (2013), United Kingdom (2011-2012), United States (2011-2012), European Union (2011-2012)	• Self-reported core skills	• List of hard-to-fill occupations and vacancies available • List of hard-to-find core skills • List of hard –to-find technical skills
Skills Towards Employment and Productivity (STEP)	World Bank	China, Yunnan Province (2012)	• Self-reported core skills • Self-reported technical skills	• Stocktakes the cognitive and job-relevant skills that workers are of existing occupations are currently using • • Ranking of cognitive and job-relevant skill needs on new hires by order of importance
School-to-Work Transition Survey (SWTS)	ILO	Brazil (2013), Russian Federation (2012 and 2015)	• Degree of match between the level of qualifications held and the level required for the job	• List of hard-to-fill occupations and vacancies available • Level of core skills of job applicants • Information on on-the-job training of workers

European skills and jobs survey (ESJS)	Cedefop	1st wave (2014) - EU27 + UK 2nd wave (2021) – EU27 + Norway + Iceland	• Self-reported core skills • Self-reported technical skills • Degree of match between the level of qualifications held and the level required for the job • Degree of match between the level of skills held and the level and frequency of the skill required for the job	Not applicable

▶ Table 4: Country abbreviations

Country abbrevation	Country
ARG	Argentina
AUS	Australia
BRA	Brazil
CAN	Canada
CHN	China
DEU	Germany
FRA	France
GBR	United Kingdom
IDN	Indonesia
IND	India
ITA	Italy
JPN	Japan
KOR	Korea
MEX	Mexico
RUS	Russia
SAU	Saudi Arabia
TUR	Turkey
USA	United States
ZAF	South Africa

▶ Annex B

An illustrative analysis of contextual indicators and their **relevance to skills demand and supply**

Employment to population ratio, Unemployment rate, Labour force participation rate

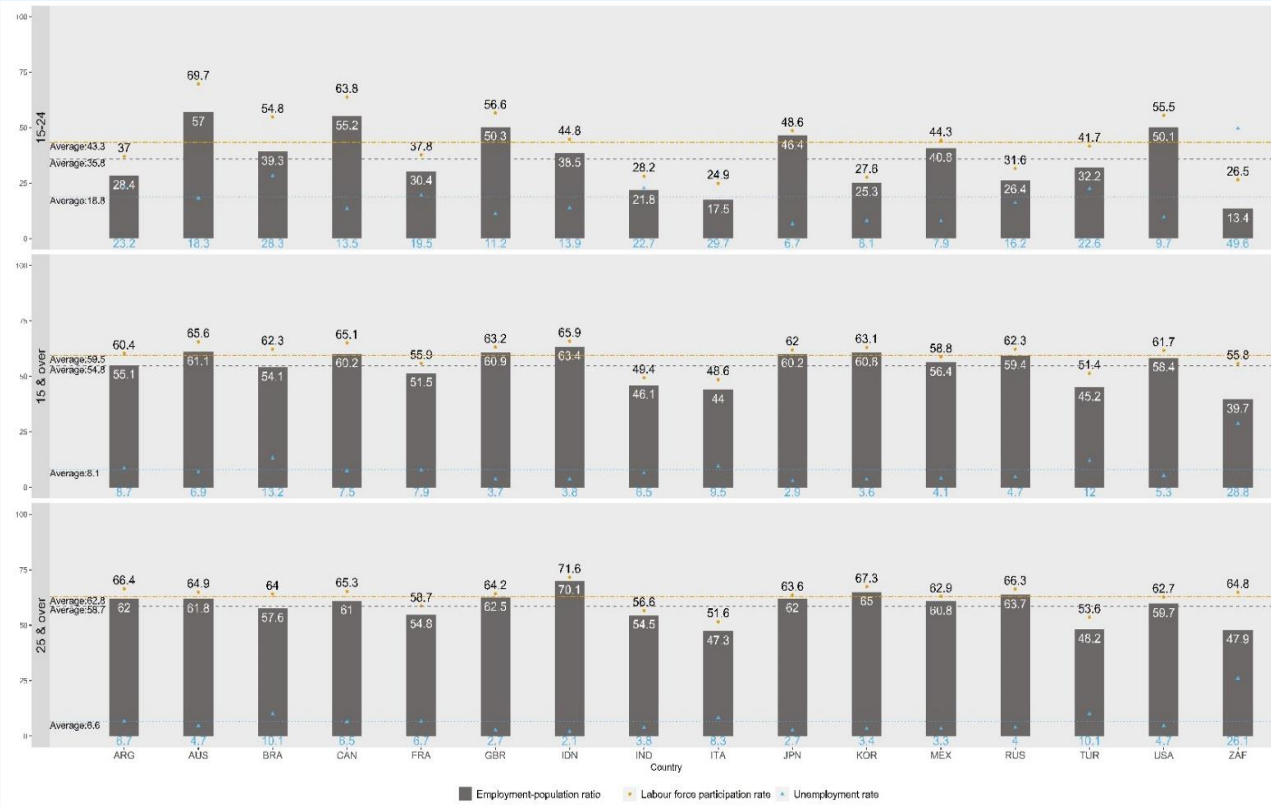
The employment to population ratio is the share of the working age population that is employed, a measure of the degree of labour utilisation and the ability of the economy to generate jobs. It is mostly influenced by cyclical factors (i.e. recessions/economic growth). A high ratio means that a large proportion of a country's population is employed, while a low ratio means that a large share of the population is not involved directly in market-related activities, because they are either unemployed or out of the labour force altogether. A low employment to population ratio could indicate that workers might not be able to find employment that matches their skills and may choose to not participate in the labour force. On the other hand, the ratio could be high for reasons that are not necessarily positive – for example, where education options are limited, young people tend to take up any work available rather than staying in school to build their human capita.

The overall unemployment rate for a country is a widely used measure of its unutilized labour supply. It reflects the proportion of the labour force that does not have a job but is available and actively looking for work. The unemployment rate is more responsive as it is affected by voluntary changes in the level of participation in the labour force as well as seasonal or cyclical variations. Its interpretation should not be independent of other indicators as a falling unemployment rate may not be strictly positive in case it is influenced by an increase in the number of discouraged workers, whose employability may further deteriorate in a long run. A high unemployment rate indicates that there exists a surplus of workers with a weak demand for their skills. A low unemployment rate may also indicate that workers may have given up seeking a job that matches their skills. To be more useful for informing skills policies, the indicator should be disaggregated by level of education, duration of unemployment, sex, work experience, etc.

The labour force participation rate indicates the proportion of the working-age population that is employed or actively looking for work, it indicates the total supply of labour. It plays a central role in the study of the factors that determine the size and composition of a country's human resources and in making projections of the future supply of labour. The information is also used to formulate employment policies, to determine training needs, to calculate the expected working lives of the male and female populations and the rates of accession to, and retirement from, economic activity.

Should there be conflicting signals in both the labour force participation and the unemployment rate, the net-impact is summarised by the employment to population ratio. It is important to note that in addition to skills mismatches, these indicators are also affected by changing workplace trends, government policies, economic conditions, social and cultural norms, labour market frictions such as minimum wages and occupational licensing requirements as well as demographic factors.

▶ **Figure 9. Labour market indicators by age group, by country**



Notes: Data for CHN, DEU and SAU are not available. Data refer to 2021 except for AUS, JPN (2020) and GBR, IND (2019). When comparing the results across countries, it is important to consider the underlying economic and social contextual factors as well as the variations in operational definitions and inclusivity of indicators.

Source: ILO database, ILOSTAT. Available from https://ilostat.ilo.org/data/.

A lower-than-average labour force participation rate with a higher-than-average unemployment rates exists for youths (15-24) in Argentina, France, India, Italy, Turkey and South Africa as well as those aged 25 and over in France, Italy, Turkey and South Africa. It is suggestive of a weak labour market where there are limited employment opportunities especially for young people, who may therefore be kept in unemployment or decide to exit the labour market as students or discouraged workers. Workers are unable to find employment that is well-matched to their skills, some of them dropping out of the labour force completely. For youths in Korea, the lower-than-average employment-population ratio is mainly driven by the low labour force participation rate rather than a high unemployment rate.

Across all age groups, the unemployment rate for South Africa has the greatest deviation from the average across G20 countries. This signals surplus of labour as compared to the jobs available with possibly weak employment creation in a context of a fast-growing labour force and/or an education and training system that may not provide workers with the right skills and qualifications demanded by the labour market.