SkillsPULSE

SKILLS - PREDICTING, UNDERSTANDING, AND LOCATING SHORTAGES IN EUROPE

D6.2 Technical report for the European Skill Deficiencies Index (ESDI)

-SUMMARY-

Dissemination level: PU

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Table of content

Abbreviations

ECS: European Company Survey

EWCS: European Working Conditions Survey

ESJS: European Skills and Jobs Survey

EU: European Union

ESI: European Skills Index

ICT: Information and Communication Technology

ILO: International Labour Organization

ISCO: International Standard Classification of Occupations

NACE: Statistical classification of economic activities in the European Union

NUTS: Nomenclature of territorial units for statistics in the European Union

OaSIS: Occupational and Skills Information System

OECD: Organisation for Economic Co-operation and Development

PES: Public Employment Services

SEN: Sensitive

STAS: Short-term anticipation of skills trends and VET demand dashboard

UK: United Kingdom

WP: Working Package

1. Introduction and study objectives

This report documents the development of the European Skills Deficiencies Index (ESDI), designed to benchmark EU member states' experience of skills deficiencies. To support the monitoring of labour market developments over time, the indicator is intended to be produced consistently across multiple years, enabling the analysis of trends and changes in skill deficiency risks. In addition, the composite indicator seeks to generate added value for policymakers and stakeholders while remaining methodologically robust and operationally sustainable. A key design principle is replicability: the indicator should be straightforward to reproduce within an automated system, allowing the tool developed under WP7 to update the results with minimal external input and intervention.

The construction of the index follows the methodological recommendations of Nardo et al. (2008), reiterated and improved by Beck et al. (2015) and more recent literature. Therefore, several steps are followed and documented in this report, namely:

1. Definition of the conceptual framework
2. Selection of indicators
3. Data treatment
4. Normalisation
5. Weighting, aggregation and statistical coherence
6. Data sensemaking and visualisation
7. Robustness and sensitivity analysis

To begin with, the conceptual framework and choice of indicators is done following a scholarly literature review and reviews of national and supra-national level composite indicators and skills intelligence systems. The conceptual choices were discussed with SkillsPULSE partners, researchers, policy makers, trade unions, and employers' organisations during a series of stakeholder workshops and engagement events. These consultations provided valuable insights into the challenges and information needs of key skills stakeholders, thereby helping to ensure the relevance and policy usefulness of the indicator. The process is discussed in detail in the sections "Conceptual framework" and "Selection of indicators."

To continue, the selection of data sources, together with the procedures for data extraction and cleaning, are presented in the "Data and methodology" section. The same section outlines and justifies the methodological choices adopted in constructing the composite indicator. Subsequently, the results are presented and discussed. Finally, robustness and sensitivity analyses are conducted to assess the impact of alternative methodological assumptions, demonstrating the limited sensitivity of the index rankings to these choices.

The composite indicator is calculated at the country level. In addition, the indicator is replicated at the occupation level to provide EU-27-wide rankings of occupations. While the occupational indicator follows the same conceptual framework as the country-level index, it is constructed using only those variables for which occupation-specific data are available. Consequently, the occupational results should be interpreted as a partial application of the broader framework, reflecting data availability constraints at the occupational level.

Lastly, ESDI is supported by two other composite indicators - Structural Labour Market Pressure Index (SLMPI) and Mitigating Factors Index (MFI). Firstly, SLMPI benchmarks the EU-27 countries according to labour market trends, technological shifts and demographic evolution. It aims to give policymakers a perspective on current pressures that may challenge future labour markets. Second, MFI benchmarks European countries based on the performance of the educational system, aiming to provide a perspective on the skills formation. Policy implications, limitations, and future research directions are discussed in the last section of this report.

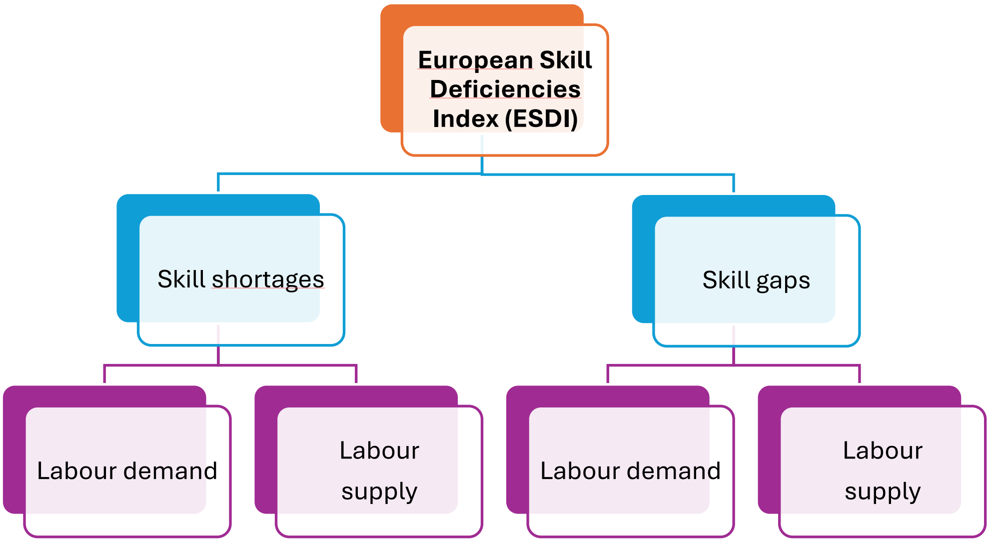
2. Conceptual framework

The European Skills Deficiencies Index (ESDI) aims at benchmarking the incidence of skills deficiencies at the EU27 level and the UK. In this context, skills deficiencies are understood as both skill shortages and skill gaps, where:

- Skill shortages refer to situations where there are no qualified candidates to fill vacant positions.
- Skill gaps arise when existing employees are deemed to lack the necessary skills for their jobs. (Shah and Burke, 2005)

Therefore, the index comprises two pillars: Skill shortages and Skill gaps. Each one of the two pillars is formed by measures pertaining from the labour demand-side and from the labour supply-side, respectively (see Figure 1 below).

Figure 1. *Conceptual framework of the European Skills Deficiencies Index (ESDI)*



To ensure a robust and comprehensive assessment, each dimension incorporates both subjective and objective indicators of labour supply and demand. Subjective indicators rely on direct feedback from employees or employers regarding perceived skills shortages or gaps, thereby providing valuable first-hand insights into workplace challenges. In contrast, objective indicators draw on empirical data — primarily job vacancy data and other statistical sources — to provide quantifiable evidence in the labour market. All variables included in this sub-index contribute positively to skills deficiencies, meaning that higher values correspond to more pronounced shortages or gaps.

The combined use of these two types of measures helps mitigate their individual limitations. Subjective indicators, while rich in contextual detail, are constrained by limited data availability across countries and low survey frequency (often every 4 to 6 years), which restricts timely updates; additionally, both employees and employers may over- or under-estimate the severity of skills deficiencies (see, for e.g., Cedefop, 2015). On the other hand, objective indicators benefit from broader and more frequent data availability but tend to capture skills deficiencies only indirectly (McGuinness et al., 2025). Bringing these approaches together therefore allows for a more balanced and reliable measurement of current skills deficiencies. The final list of indicators is presented in Table 1 below.

Table 1. *European Skills Deficiencies Index (ESDI) - structure*

Pillar	Dimension	Indicator [Source]	Direction
Skill shortages	Labour demand	Employer-reported hiring difficulties [based on ECS]	+ (e.g., Tang and Wang, 2005; Gambin et al., 2016)
		Potential shortage-affected vacancy share (SkillsPULSE indicator)	+ (McGuinness et al., 2026)
	Labour supply	**Employee share in potential shortage-affected jobs** (SkillsPULSE indicator)	+ (McGuinness et al., 2026)
		Job openings per unemployed person [based on Eurostat]	+ (e.g., OECD: Labour market pressure for skills-first approaches index)
Skill gaps	Labour demand	Employer-reported under-skilling [based on ECS]	+ (e.g. Forth and Mason, 2006)
	Labour supply	Employee-reported under-skilling [based on EWCS/ESJS]	+ (e.g. McGuinness et al., 2024; McGuinness and Staffa, 2025)
		Employee undereducation [Ilostat]	+ (e.g. Quintini, 2011; McGuinness et al., 2018)

3. Data and methodology

The analysis covers the EU-27 Member States and the United Kingdom over the period 2015–2024, or the latest year for which data are available. Data were initially collected for the period 2015–2025; however, at the time of extraction and indicator computation, 2024 was the latest available year for most indicators. To ensure consistency across indicators, the reference period was therefore restricted to 2015–2024. Data coverage is not fully uniform across countries, with the United Kingdom exhibiting particularly significant gaps: for many indicators, the latest available year is 2019. To ensure its inclusion in the index, missing values for subsequent years were imputed using the latest available observations. This implies that UK index values are to be treated with caution as they mostly represent pre-COVID19 context.

Missing values are handled using linear interpolation or cold deck imputation, depending on the data availability. Linear interpolation is applied when missing values occur between known observations, allowing them to be estimated based on a linear trend across adjacent years, whereas cold-deck imputation is used when such interpolation is not feasible, meaning that any missing value is replaced with the corresponding value from the previous or latest available year.

To detect **outliers**, variables whose absolute skewness exceeds 2 and whose kurtosis exceeds 3.5 are flagged for further inspection (Becker et al., 2019). This is done for each year separately. The *Potential shortage-affected vacancy share* and *Job openings per unemployed person* variables are flagged.

In case of each one of these variables, an evaluation is conducted to determine whether the extreme values are genuine observations or the result of reporting or exporting errors. Given that, in both of the flagged cases, the observed values reflect a genuine period of labour market tightness and relative outperformance, the series was not winsorised, in order to preserve this effect in the index.

Sensitivity analysis will also account for the alternative of treating outliers through standard wisorisation or through COIN Tool log-transformation. These aspects will be discussed at length in the robustness section.

The indicators included in the index have different measurement units and therefore, scales. Hence, to be able to aggregate them in a meaningful way, they were first **normalised** to reach a common scale. The most common approach was used – min-max normalisation:

$$x_{min-max_{i,cy}} = \frac{x_{i,cy} - min(x_i)}{min(x_i) - max(x_i)} \cdot 100$$

where:

- $x_{min-max_{i,cy}} = the\ min\text{-}max\ scaled\ value\ of\ indicator\ i\ in\ country\ c\ in\ year\ y$
- $min(x_i) = the\ lowest\ value\ of\ indicator\ i$
- $max(x_i) = the\ highest\ value\ of\ indicator\ i$

Thus, all variables were rescaled to a 0–100 range, where the minimum observed value across countries and years is assigned a value of 0 and the maximum a value of 100. Indicators are normalised based on the observed minimum and maximum values across all countries during the reference period 2015–2024. These goalposts are held constant for subsequent updates in the tool to be constructed by WP7.

At this stage, the directionality of each indicator is also taken into account. Both the “Skill shortages” and “Skill gaps” pillars and their constituting indicators are positively associated with the overall index, as higher levels of current skill shortages and skill gaps are linked to a greater skills deficiencies.

In terms of **weighting and aggregation**, the baseline model employs an equal-weight arithmetic aggregation approach across all levels. This method is appropriate when there is no strong theoretical justification for assigning differential weights to the underlying components. Furthermore, the use of an arithmetic mean implies full compensability between the two pillars (see, e.g., Nardo et al., 2008), allowing a lower score in one dimension to be offset by a higher score in the other. This assumption is suitable in the present context, as skill shortages and skill gaps are considered equally important and jointly constitute the overall measure of skills deficiencies.

Therefore:

$$ESDI_{c,y} = \frac{\sum_{j=1}^{n} Pillar_{j c,y}}{n};\ Pillar_{j_{c,y}} = \frac{\sum_{k=1}^{m} Dimension\ _{k c,y}}{m};\ Dimension_{k_{c,y}} = \frac{\sum_{l=1}^{p} Indicator_{l_{c,y}}}{p}$$

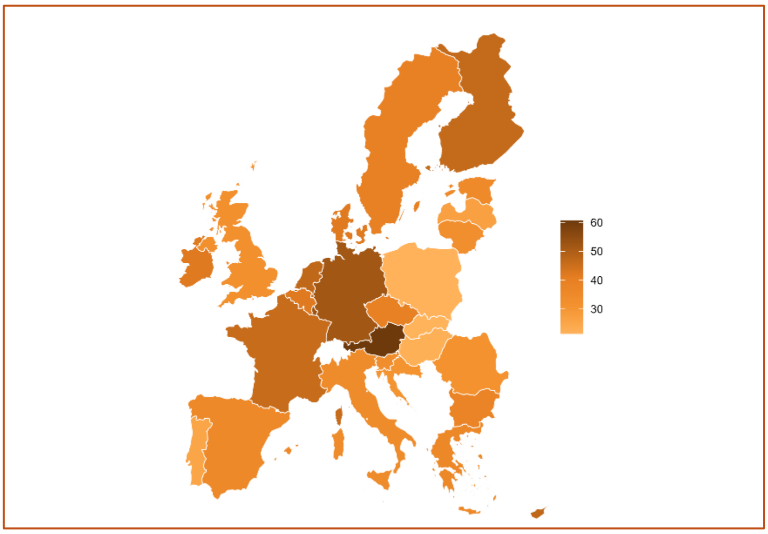
where:

- $ESDI_{c,y} = ESDI\ score\ of\ country\ c\ in\ year\ y$
- $Pillar_{j_{c,y}} = score\ pillar\ j\ of\ country\ c\ in\ year\ y$
- $Dimension_{k_{c,y}} = score\ dimension\ k\ in\ country\ c\ in\ year\ y$
- $Indicator_{l_{c,y}} = score\ dimension\ l\ in\ country\ c\ in\ year\ y$
- $m = number\ of\ dimensions$
- $p = number\ of\ indicators$

4. Results and interpretation

Figure 2 presents the EU27 and UK 2024 country scores in the European Skills Deficiencies Index (ESDI). The results seem to indicate that Austria, Malta, and Luxembourg exhibit the highest levels of current skills deficiencies in 2024. In contrast, Hungary, Poland, and Slovakia display the lowest levels of current skills deficiencies.

Figure 2. *Distribution of the European Skills Deficiencies Index (ESDI) scores, 2024*

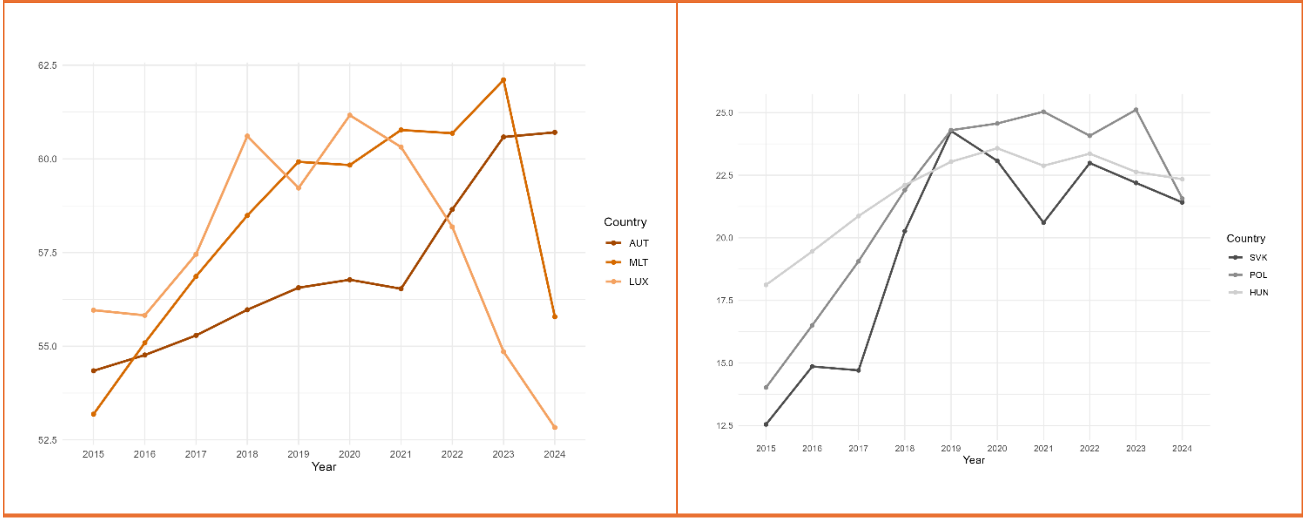


Note: Data coverage is not fully uniform across countries, with the United Kingdom exhibiting particularly significant gaps: for many indicators, the latest available year is 2019. Therefore, UK scores for 2020–2024 may reflect pre-COVID19 labour market conditions.

Figure 3 shows the evolution of top three countries in European Skills Deficiencies Index (Austria, Malta, and Luxembourg) during the 2015-2024 period. From 2021 onwards a decreasing trend is observed in case of Malta and Luxembourg, while Austria is increasing. Figure 3 also shows the three countries that have the lowest skills deficiencies (Slovakia, Poland, and Hungary). In all the three cases, varying performances are observed throughout the 10 years of analysis.

Figure 3. *Evolution in European Skills Deficiencies Index (ESDI)*

Top 3 countries	**Bottom 3 countries**



5. Robustness analysis

This section presents the results of the sensitivity analysis assessing the joint uncertainty associated with methodological choices related to winsorisation, normalisation, weighting, and aggregation.

First, uncertainty in the treatment of outliers is represented by alternative specifications ranging from no treatment to winsorisation of up to five observations. Second, indicator values are normalised using either min–max rescaling or z-score standardisation. Third, uncertainty in the weighting scheme is evaluated through random perturbations of baseline weights at pillar and index level within ±25%. Finally, uncertainty in the aggregation procedure is assessed by comparing arithmetic and geometric aggregation at the overall index level.

The sensitivity analysis is based on 5,000 Monte Carlo replications, generating 30,000 rankings, while confidence intervals for the sensitivity indices are estimated using 1,000 bootstrap resamples. It is restricted to the 2024 cross-section and is not extended to the full 2015–2024 period. This is due to computational constraints and the current implementation of COINr which is used for this section and does not support sensitivity analysis for panel data.

Table 2 presents the Sobol sensitivity indices. They show that the composite indicator is primarily affected by the normalisation method and, to a much lesser extent, by the weighting scheme. The normalisation method explains 82% of output variance as a main effect and 89% when interaction effects are included, making it the most influential methodological choice. Weighting scheme is the second most influential factor (Si = 0.11; STi = 0.12). The aggregation scheme has only a modest effect (Si = 0.03; STi = 0.04), while the winsorisation shows no measurable influence. This suggests that the treatment of the outliers identified before does not have an impact on the ranking of the countries. Overall, the results suggest that uncertainty in the composite indicator is driven mainly by decisions regarding normalisation and weighting rather than aggregation.

Table 2. *Sobol sensitivity indices*

Uncertainity source	Si	STi	Si_q5	Si_q95	STi_q5	STi_q95
Winsorisation	0	0	0	0	0	0
Normalisation	0.82339	0.889519	0.757986	0.888864	0.863386	0.915214
Weights	0.104504	0.115284	0.07879	0.13153	0.111106	0.119295
Aggregation	0.027177	0.043062	0.012731	0.041908	0.040915	0.045165

The average absolute rank shift from initial ranking across all countries, calculated across the 30,000 simulations, is 1.87. This indicates that, on average, a country's position changes by almost two ranks as a result of variations in weighting, normalisation, winsorisation, and aggregation methods. The largest average rank shift is observed for Greece (4.46 ranks), followed by Czechia (4.31 ranks) and Spain (4.05); on the other hand, the lowest rank shifts are in case of Luxembourg (0.63), Poland (0.41), and Austria (0.21). Overall, 9 out of the 28 countries have an average rank shift of less than one position, and a further 8 countries shift by between one and two positions. Moreover, the initial rankings are highly (and statistically significant) correlated with the mean and median ranks across the 30,000 alternative simulations (Spearman correlation coefficient: 0.96).

Table 3 provides the baseline and median ranks together with the 90% simulation intervals obtained from the 30,000 specifications. The intervals are generally narrow for the highest-ranked countries, with the first four countries having intervals spanning no more than three ranking positions. Greater uncertainty is observed towards the middle of the distribution, particularly for Ireland (baseline rank 10), Denmark (11), Bulgaria (14), Greece (15), and Spain (16), whose intervals span between nine and twelve positions. Even in these cases, however, the median rank remains close to the baseline: the difference between the baseline and median ranks is between zero and three positions for all countries except Greece and Spain, whose median ranks are five positions higher than their baseline rank.

Table 3. *ESDI - baseline, median ranks and 90% simulation intervals*

Country	Original rank	Median rank over 30,000 simulations	90% interval over the 25,000 simulations
Austria	1	1	[1; 2]
Malta	2	4	[2; 5]
Luxembourg	3	3	[1; 4]
Germany	4	3	[2; 4]
Cyprus	5	8	[5; 11]
Netherlands	6	5	[4; 7]
Finland	7	8	[6;10]
France	8	7	[7; 9]
Belgium	9	11	[9; 12]
Ireland	10	13	[9; 18]
Denmark	11	14	[9; 21]
Sweden	12	11	[9; 13]
Czechia	13	9	[6; 13]
Bulgaria	14	13	[8; 18]
Greece	15	20	[14; 24]
Spain	16	21	[14; 24]

Estonia	17	14	[11; 18]
Italy	18	16	[14; 18]
Slovenia	19	18	[15; 19]
Lithuania	20	20	[16; 23]
United Kingdom	21	23	[18; 25]
Romania	22	20	[16; 22]
Croatia	23	21	[19; 23]
Latvia	24	24	[22; 24]
Portugal	25	25	[22; 25]
Hungary	26	27	[26; 28]
Poland	27	27	[27; 28]
Slovakia	28	27	[26; 28]

Note: Simulation intervals represent the central 90% of the rank distribution across 30,000 simulated scenarios based on alternative normalisation methods, random weight perturbations within ±25% of the baseline weights, alternative aggregation formulas at the pillar-to-index level, and treatment of outliers.

Overall, the sensitivity exercise indicates that, although normalisation, weighting and aggregation choices contribute to uncertainty in the numerical value of ESDI, their impact on country rankings is limited. The results therefore support the robustness of the relative country positions under reasonable alternative methodological assumptions. Countries with comparatively wider simulation intervals – particularly Spain and Greece – should nevertheless be interpreted with somewhat greater attention to the precise rank position, while the broader positioning of countries in the ranking remains highly stable.

6. Occupation-level case study

The composite index is replicated at occupational level to facilitate benchmarking according to the magnitude of skills deficiencies. However, owing to data constraints at the time of the study, the analysis is confined to the EU-27 aggregate and is not extended to identify deficient occupations at the country level.

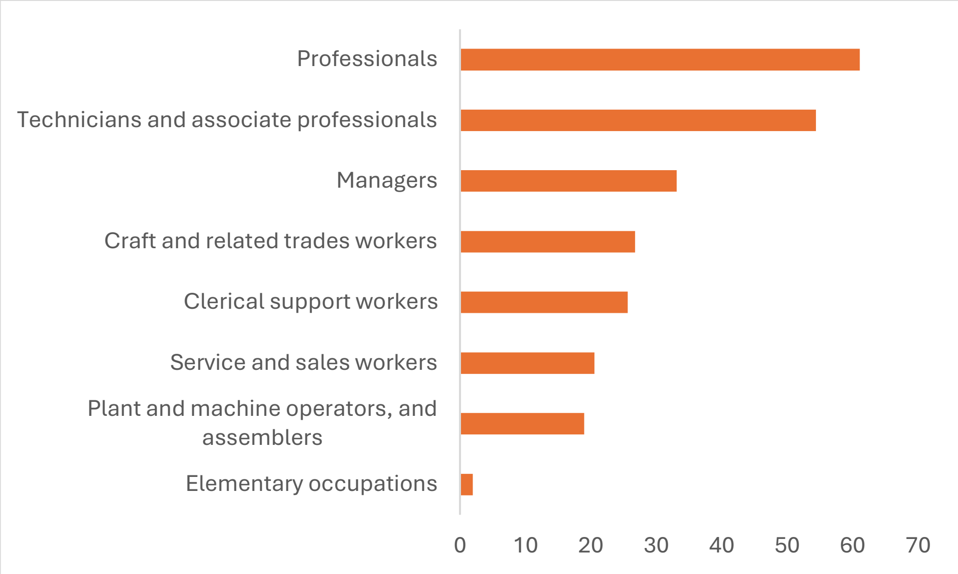
In particular, concerns regarding statistical reliability were raised for the variable capturing the employee share in potential shortage-affected jobs, derived from ESJS data, due to the limited number of observations per country–occupation. For instance, in many countries, the number of respondents classified as skilled agricultural, forestry, and fishery workers is fewer than ten. As the construction of this variable requires identifying employees within a given occupation and country who also satisfy seven additional criteria related to job complexity, seniority, and wage, such small sample sizes render the resulting estimates insufficiently robust for statistically reliable inference. Similar concerns, albeit less stringent were raised in case of all variables created based on survey questions.

Since several indicators are not available at occupational level the conceptual framework is adapted for the occupational ESDI. This is the case for the employer-reported variables (hiring difficulties and under-skilling) are not available for occupational groups. To our knowledge, the Flash Eurobarometer 529 (European Commission) addressed the employer-reported hiring difficulties for different occupational groups. However, the survey does not cover all the occupational groups, making it unsuitable for the construction of this composite index. Furthermore, while the WP4 survey did address the employer-reported variables including the occupational lens, the survey covered only a selection of countries, making it unsuitable for an EU-level estimate.

Lastly, the analysis is done for ISCO-1 digit groups due to more data availability than in case of sub-major groups. ISCO 0 (Armed forces occupations) and 6 (Skilled agricultural, forestry and fishery workers) are not represented in the Potential shortage-affected vacancy share (Lightcast) and Employee share in potential shortage-affected jobs (ESJS) due to data limitations. Therefore, they are removed from the sample. Moreover, data on job openings per unemployed persons should be taken with caution since the job vacancies per occupation did not cover all EU27 member states.

Figure 5 shows the distribution of occupations according to the European Skills Deficiencies Index in 2024. Accordingly, Professionals, and Technicians and associate professionals are the two occupations that face the highest skills deficiencies levels. On the other hand, Elementary occupations face lower skills deficiencies.

Figure 4. *Occupational ESDI scores 2024*



A potential limitation of the analysis concerns the use of Lightcast data, as online job vacancy data may disproportionately capture office-based occupations and therefore introduce bias into the results. While a robustness check excluding the Lightcast indicator yields index scores that remain highly consistent across years (correlation coefficient of 0.97), the reliance on online vacancy data should nonetheless be acknowledged as a limitation. Consequently, the findings should be interpreted with caution, particularly given the possibility that certain occupations may be underrepresented in online job postings.

7. Sector-level case study

The composite index is replicated at sectoral level to facilitate benchmarking according to the magnitude of skills deficiencies. Similar to the occupation-level index, owing to data constraints at the time of the study, the analysis is confined to the EU-27 aggregate and is not extended to identify deficient sectors at the country level.

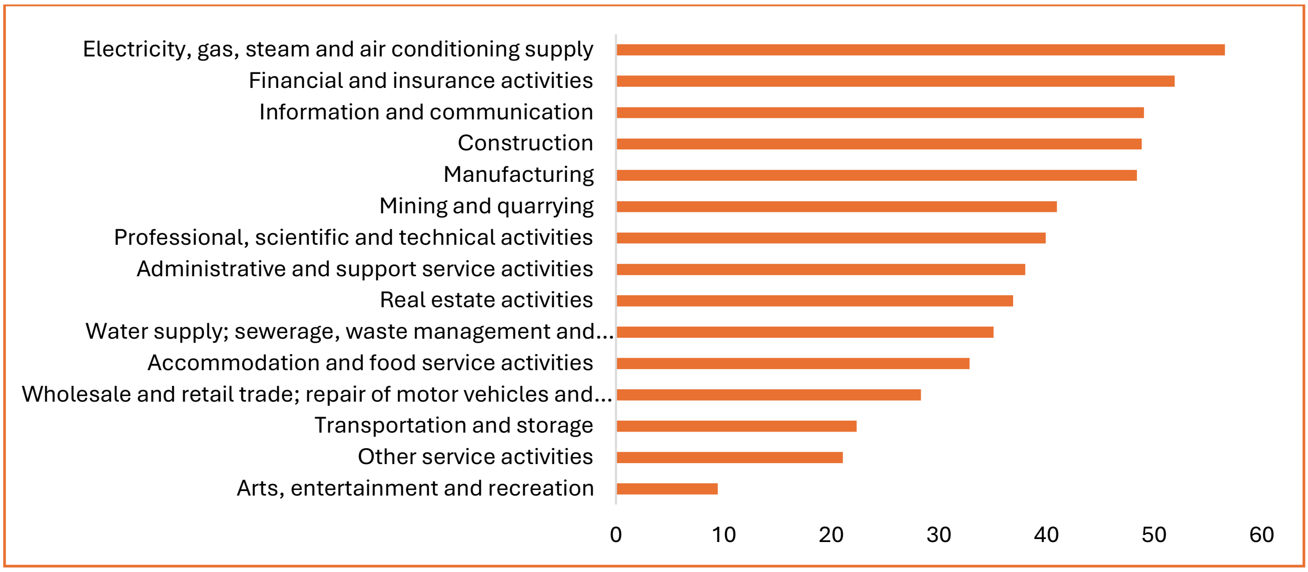
Since several indicators are not available at sectoral level the conceptual framework is adapted for the sectoral ESDI. First, this is the case for the Job openings per unemployed person variable. Such an indicator cannot be computed using current available data as the sector the unemployed person worked in previously is not available. Second, the undereducation variable from Ilostat merge NACE sections together, making it difficult to be used in the current index.

In addition, several sectors are excluded due to limited data coverage. These are sectors A ("Agriculture, forestry and fishing"), O ("Public administration and defence; compulsory social security"), P ("Education"), Q ("Human health and social work activities"), T ("Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use"), and U ("Activities of extraterritorial organizations and bodies"). They are only covered by ESJS, EWCS, and Lightcast.

One outlier is found in the case of Employee reported under skilling variable. This is the case of sector B ("Mining and quarrying") in 2021. Upon careful examination the value was kept. For most sectors the ESJS values in 2021 seem to be higher than the EWCS values in 2015. This might be due to the increased technological skill requirements generated by the natural technological advancements and the change in the workplace following the COVID19 pandemics.

Figure 6 shows the distribution of sectors according to the European Skills Deficiencies Index in 2024. Accordingly, the "Electricity, gas, steam and air conditioning supply" and the "Financial and insurance activities" are the two sectors that face the highest skills deficiencies levels. On the other hand, "Arts, entertainment and recreation" face lower skills deficiencies.

Figure 5. *Sectoral ESDI scores 2024*



8. Complementary composite indicators

Two complementary composite indicators are developed to add to the context of skill needs formation and skill formation. These are the Structural Labour Market Pressures Index (SLMPI) and the Mitigating Factors Index (MFP). First, the Structural Labour Market Pressure Index accounts for structural labour market factors that exert a pressure on skill demand likely supporting the persistence/emergence of skill shortages and gaps in the future. For a more comprehensive approach, these factors are related to both technological shifts and labour market trends. Second, the Mitigating Factors Index accounts for educational outcomes that have a role in skills formation and therefore, might have a mitigating effect on the skills deficiencies.

8.1. The Structural Labour Market Pressures Index (SLMPI)

The Structural Labour Market Pressures Index is constructed of two pillars – Technological shifts and Labour market trends. The detailed structure of the index (pillars, dimensions, and base indicators) is described in Table 4.

Table 4. *Structural Labour Market Pressure - structure*

Pillar	**Dimension**	**Indicator** (Source)	**Direction**
Technological shifts	Internal innovation	Patent applications (based on Eurostat)	+ (e.g., Horbach and Rammer, 2022)
	Technology adoption - enterprises	AI adoption in enterprises (based on Eurostat)	+ (e.g., Quintini, 2011)
		Rise of technical skills in digital occupations **(SkillsPULSE indicator)**	+ (e.g., WP2)
Labour market trends	Labour market trends	Employment growth (based on Eurostat)	+ (e.g., Cedefop: Short-term anticipation of skills trends and VET demand dashboard)
		Working hours growth (based on Eurostat)	+ (e.g., Hayes and Oxford Economics: Hayes global skills index)
		Working age population growth (based on Eurostat)	- (e.g., Kahlenberg and Spermann, 2012)

Similar to ESDI, missing data are handled using linear interpolation or cold deck imputation, depending on the data availability. Further on, outliers are detected using skewness and kurtosis thresholds. *Patent applications* are flagged for 2016 and 2017. In both instances, Luxembourg emerged as a high outlier. Examination of the original time series confirmed that Luxembourg genuinely outperformed in these years, followed by a subsequent decline. These values are therefore not the result of reporting or processing errors. Because the outliers reflect true performance differences rather, they are retained in the dataset to preserve meaningful variation across countries, in line with Becker et al. (2019).

To continue, one high outlier is identified in case of the *Employment growth* series – Malta (2018). Examination of the underlying employment data (lfsa_eisn2) indicates that this observation reflects a genuine increase rather than a data anomaly. Malta appears to significantly outperform other countries during this period. Consequently, the outlier is retained and not adjusted (see, for example, Becker et al., 2019).

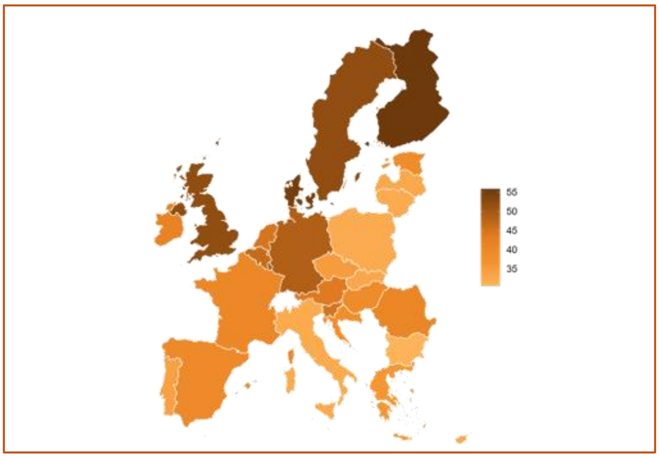
Finally, Malta is identified as a high outlier in 2020 and 2024 for the *Working population growth* variable. Although a marked decline is observed in 2021 and 2022—likely reflecting the impact of the COVID-19 pandemic—the overall evolution of the time series appears natural in the remaining years.

As the observed pattern is considered to reflect genuine dynamics rather than data anomalies, the series is not winsorised.

Min-max normalisation is used to bring all variables to a common scale. All indicators, except for the *Working age population growth* are positively directed as they exert pressures on the skill needs. *Working age population growth* is negatively directed as a larger labour force is likely to increase the availability of workers and alleviate skill shortages, thereby reducing the pressure for additional skills development and workforce adaptation.

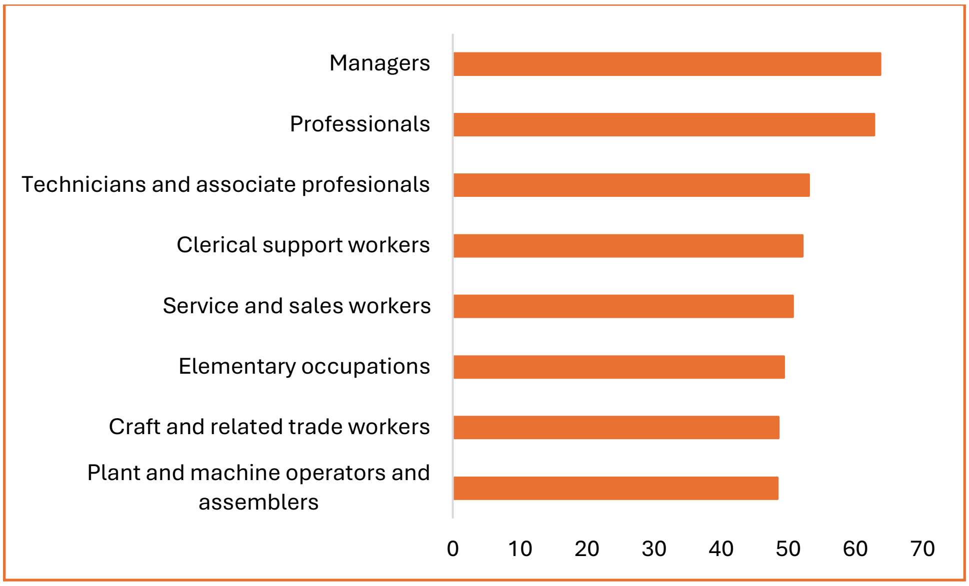
As in the case of ESDI, an equal-weight arithmetic approach is used. Results are presented in Figure 7. Highest technological and labour market pressure appears to be in Finland (55.84 out of 100), followed by Denmark and the United Kingdom (54.76 and 52.02, respectively). On the other hand, Bulgaria, Poland and Lithuania have the lowest technological and labour market pressure.

Figure 6. *Distribution of the Structural Labour Market Pressure Index (SLMPI) scores, 2024*



At occupational level, only employment growth and working hours growth are available. The 2024 results based on these two variables are exhibited in Figure 8 below. Managers and Professionals seem to face the highest labour market pressure.

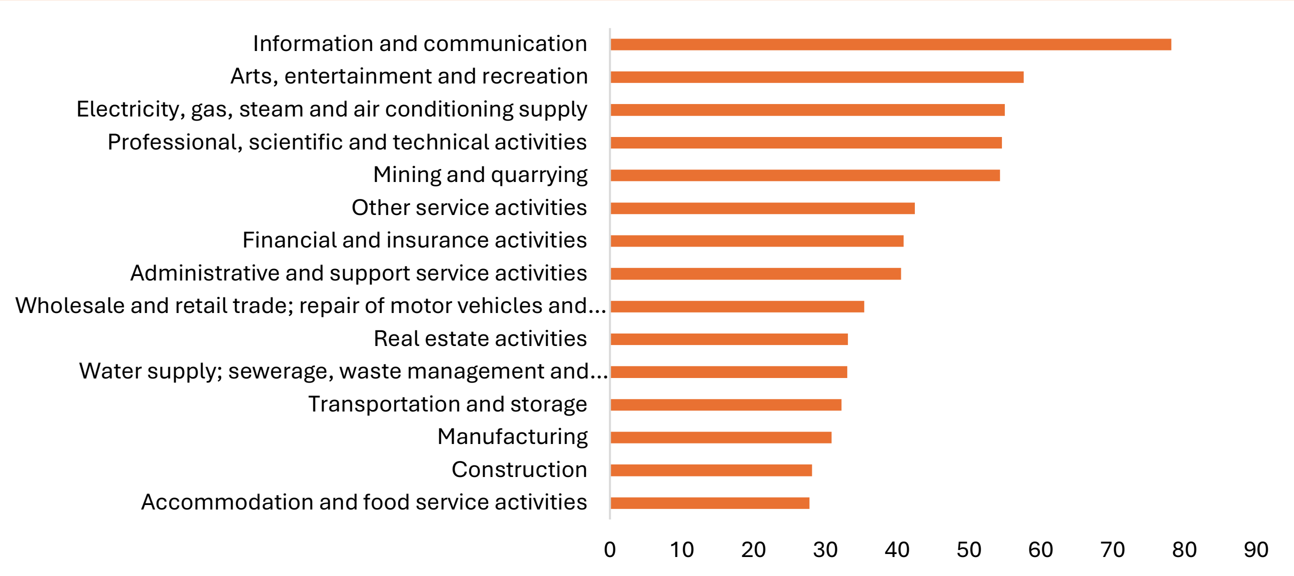
Figure 7. *The Structural Labour Market Pressure Index - occupational level, 2024*



Note: Only employment growth and working hours growth are used for computation.

At sector level, AI adoption in enterprises, Employment growth, and Working hours growth are the only available variables. The 2024 results based on these three variables are exhibited in Figure 9 below. The "Information and communication" sector seems to face the highest labour market pressure at the EU27.

Figure 8. *The Structural Labour Market Pressure Index - occupational level, 2024*



Note: Only AI adoption in enterprises, employment growth, and working hours growth are used for computation.

8.2. The Mitigating Factors Index (MFI)

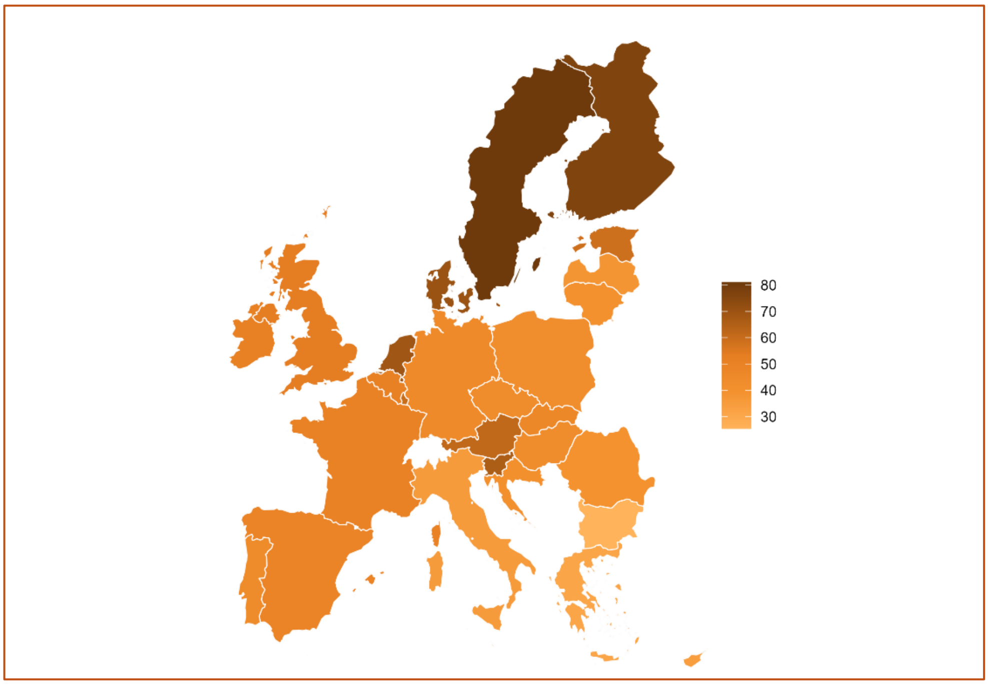
The Mitigating Factors Index (MFI) comprises two pillars – "Formal education outcomes" and "Lifelong learning." First, the "Formal education outcomes" pillar incorporated 3 measures of formal education outcomes, namely: *Tertiary education graduates*, *STEM graduates from tertiary education*, and *VET graduates from upper and post-secondary education.* First, the *Tertiary education graduates* variable is measured as the share of population with tertiary education based on Eurostat data (edat_lfse_03). Second, *STEM graduates from tertiary education* are computed as the share of STEM graduates from total tertiary education graduates (Eurostat: educ_uoe_grad02). STEM fields are considered ISCED-F 05-07. Lastly, the *VET graduates from upper and post-secondary education* are computed as share of graduates of vocational education ISCED levels 3-4 (Eurostat: educ_uoe_grad01). Since greater shares of educated people represents an improved labour market supply, these indicators will have a negative direction in the index (higher values are conducive to lower educational pressures and therefore, lower potential skills deficiencies). These measures generally relate to skill shortages.

To include an up-skilling and re-skilling component, the index uses *Participation in lifelong learning* (Eurostat: trng_lfs_11) as part of the "Lifelong learning" pillar. Data is taken from the Labour Force Survey (LFS) and measures the participation rate in education and training during the last 4 weeks of employed people aged 25 – 64 years.

In case of missing data, imputation is done through interpolation and cold-deck imputation. Further on, no outliers are identified based skewness and kurtosis thresholds. All variables are brought to a common scale through min-max normalisation over the 2015-2024 period. Each base indicator is positively directed.

Indicators are aggregated using an equal-weight arithmetic aggregation approach. Results are shown in Figure 10. Sweden, Finland, and Denmark have the best educational outcomes. Whereas Cyprus, Greece, and Bulgaria seem to be the lowest performers.

Figure 9. *Distribution of the Mitigating Factors Index (MFI) scores, 2024*



9. Conclusions and policy implications

The current report describes the construction of the European Skills Deficiencies Index (ESDI) developed under the Skills PULSE project. The index aims at benchmarking the EU Member States based on their relative levels of skills deficiencies. By doing so, the index brings several contributions to the skills intelligence tools available in the European Union.

First, the ESDI covers all the EU-27 member states and the UK providing a harmonised tool that national policy makers, education providers, and other skills stakeholders can use in conjunction with their national monitoring systems. The index enables countries to assess their performance relative to their European peers and therefore identify potential best practices from countries sharing similar structural characteristics, such as population size, or institutional arrangements.

Furthermore, ESDI complements other Skills PULSE outputs. For example, the new and emerging skills identified based on Lightcast data provide additional insights into the specific skills currently in demand, thereby enriching the interpretation of country-level skill deficiency risks.

Second, to the best of our knowledge, the ESDI is the first EU-level composite indicator that jointly measures both skill shortages and skill gaps. Previously developed indicators generally focused on skill shortages only, neglecting the skills deficiencies that pose barriers to current employees to perform their tasks efficiently. Therefore, by incorporating both dimensions, ESDI brings a broader picture of skills deficiencies challenges inside the EU member states.

Third, the index combines both objective and subjective indicators and incorporates information from both the demand and supply sides of the labour market. This multidimensional approach enhances the robustness of the measurement framework, increasing its ability to capture genuine skill shortages and skill gaps.

Finally, the index offers several methodological advantages. First, it has been designed to support meaningful time-series comparisons, enabling the monitoring of trends and changes in skills deficiencies over time. Second, it is operationally sustainable, allowing for an automated system to update the values reliably with minimal external input.

The results suggest low variation in skills deficiencies across Europe. Austria, Malta, and Luxembourg exhibit the highest levels of current skills deficiencies in 2024. In contrast, Hungary, Poland, and Slovakia display the lowest levels of skills deficiencies. At the occupational level, Professionals and Technicians and Associate Professionals appear to deal with the highest levels of skills deficiencies across the European Union. Furthermore, the sectors most impacted by skills deficiencies appear to be “Electricity, gas, steam and air conditioning supply” and the “Financial and insurance activities” sectors.

The sensitivity analysis suggests that the normalisation and weighting choices constitute the main sources of methodological uncertainty. Nevertheless, country rankings remained highly stable across alternative model specifications, with low average rank shifts and strong rank correlations. These findings provide confidence in the robustness of the results.

As any research, the European Skills Deficiencies Index is subject to several limitations. They have been addressed to the best of our knowledge. Also, several policy implications derive from them. One limitation arises from the reliance on survey-based indicators, which are not collected annually, requiring the interpolation of missing values. Moreover, in some cases, survey questions have been discontinued. For example, the European Working Conditions Survey included a skills-match question in the 2015 and 2024 waves, but not in the 2021 wave.

To mitigate this constraint, the index incorporates objective indicators available at higher frequencies. However, these measures provide only indirect evidence of skills deficiencies and cannot fully substitute for direct survey-based assessments. Consequently, the findings highlight the need for more frequent and harmonized EU-level data collection efforts aimed at measuring skill shortages and skill gaps. Such improvements would enhance the accuracy, timeliness, and policy relevance of future monitoring frameworks.

A second limitation concerns the lack of sufficiently detailed and comparable data to enable benchmarking of occupations within countries. This problem is particularly acute in the case of survey data where the number of participants is not large enough to ensure statistical significance of values if disaggregated. Again, this highlights the importance of increasing the effort for data collection through large EU-level surveys to enable better, more detailed research.

In addition, several indicators are not collected at occupational level. For example, to our knowledge there are no EU-level surveys covering skill shortages and gaps from the employer perspective that are covering all ISCO major groups. An example of such a survey was given by the SkillsPULSE WP4. However, the survey did not cover all the EU member states.

If more granular data became available, future research could focus on extending the indicator at country-occupation-sector-nuts level. Also, skills stakeholders that have the needed data can use the

Skills PULSE methodology to benchmark different units of their interest. For example, a national PES that has NUTS-level high-quality data could see which NUTS regions deal with greater skill deficiency risks. Similarly, a pan-European trade union could benchmark EU countries in terms of skills deficiencies for their specific occupation.

Furthermore, the results should be interpreted with appropriate caution due to the characteristics of some of the underlying data sources. In particular, the use of online vacancy data from Lightcast may disproportionately capture office-based and higher-skilled occupations, potentially leading to the underrepresentation of certain lower-skilled jobs and sectors.

To assess the impact of this limitation, several robustness checks were conducted, including the iterative exclusion of individual indicators. Index scores remained highly correlated with the baseline specification, while country rankings remained largely unchanged across alternative model configurations. These findings support the overall robustness of the index.

Lastly, for several indicators, data for the United Kingdom stops in 2019. Therefore, index values for recent years should be treated with caution as they may reflect pre-pandemics conditions.

In the end, two complementary composite indicators were constructed – the Structural Labour Market Pressure Index (SLMPI) and the Mitigating Factors Index (MFI). These two measures give additional context to the skill needs formation and mitigation, enabling the users of the European Skills Deficiencies Index (ESDI) to gain a more comprehensive understanding of the drivers and dynamics underlying skill shortages and skill gaps. While the ESDI captures the extent of skills deficiencies, the SLMPI provides insight into the structural labour market pressures arising from technological change and evolving labour market trends, and the MFI reflects the capacity of education and training systems to mitigate these challenges through human capital development. Taken together, the three indicators offer an integrated analytical framework for monitoring skill imbalances, identifying their underlying causes, and supporting evidence-based policy design aimed at improving labour market resilience and fostering sustainable workforce development across Europe.

References

Becker, W., Benavente, D., Dominguez-Torreiro, M., Moura, C., Neves, A., Saisana, M., & Vertesy, D. (2019). *COIN Tool: User Guide.* Publications Office of the European Union. doi:http://dx.doi.org/10.2760/523877

Cedefop. (2015). *Skill shortages and gaps in European enterprises – Striking a balance between vocational education and training and the labour market.* Publications Office.

Ferent-Pipas, M. (2024). Flexicurity in the EU28 countries: A multiyear composite indicator proposal. *Scientific Annals of Economics and Business, 71*(1), 43-74.

Forth, J., & Mason, G. (2006). Do ICT skill shortages hamper firms' performance? *National Institute of Economic and Social Research*.

Gambin, L., Hogarth, T., Murphy, L., Spreadbury, K., Warhurst, C., & Winterbotham, M. (2016). Research to understand the extent, nature and impact of skills mismatches in the economy. *Department for Business, Innovation and Skills (Research paper number 265)*.

Jackson, D., & Chapman, E. (2012). Non-technical skill gaps in Australian business graduates. *Education + Training, 54*(2/3), 95-113.

Kahlenberg, C., & Spermann, A. (2012). How Could Germany Escape the Demographic Trap? *IZA Policy Paper Series no. 48*.

Mazziotta, M., & Pareto, A. (2016). Methods for constructing non-compensatory composite indices: a comparative study. *Forum for Social Economics, 45*(2-3), 213-229.

McGuinness, S., & Ortiz, L. (2015). Skill Gaps in the Workplace: Measurement, Determinants and Impacts. *Institute of labor economics (IZA DP No. 9278)*.

McGuinness, S., & Staffa, E. (2025). Measuring the Incidence and Impacts of Skill Gaps Among European Workers. *Institute of labor economics (IZA DP No. 17993)*.

McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills mismatch: Concepts, measurement. *Journal of Economic Surveys, 32*(4), 985-1015.

McGuinness, S., Staffa, E., & Redmond, P. (2024). Is there a skills problem in Europe?, Rethinking Europe's Skill Needs: Reflections following the European Year of Skills. *Quaderno 67 Fondazione Giacomo Brodolini*.

McGuinness, S., Staffa, E., Kelly, L., Redmond, P., & Lee, S. (2026). Developing a new European indicator of potential skill shortages. *Applied Economics*, 1-20.

McGuinness, S., Staffa, E., Lee, S., Kelly, L., & Redmond, P. (2025). Developing a New European Indicator of Potential Skill Shortages. *Institute of Labor Economics (IZA DP No. 18133)*.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffmann, A., & Giovannini, E. (2008). *Handbook on constructing composite indicators: methodology and user guide.* Paris: OECD Publishing. Retrieved from https://www.oecd.org/els/soc/handbookonconstructingcompositeindicatorsmethodologyanduserguide.htm

Quintini, G. (2011). Over-Qualified or Under-Skilled: A Review of Existing. *OECD Social, Employment and Migration Working Papers No. 121*.

Saisana, M., & Salteli, A. (2026). Sensitive issues in the development of composite indicators for policy-making. *Simulation in Industry and Services.* Brussels.

Saisana, M., Saltelli, A., & Stefano, T. (2005). Uncertainity and sensitivity analysis tecniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 168*(2), 307-323.

Shah, C., & Burke, G. (2005). Skills shortages: Concepts, measurement and policy responses. *Australian Bulletin of Labour, 31*(1), 44-71.

Tang, J., & Wang, W. (2005). Product Market Competition, Skill Shortages and Productivity: Evidence from Canadian Manufacturing Firms. *Journal of Productivity Analysis, 23*(3), 317-339.

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