

Identifying Skill Mismatch Patterns in Europe: A Multivariate Statistical Approach

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Please cite this paper as:

Ghita, S.I., Boboc, C.R., Saseanu, A.S., & Mihai, M. (2026). Identifying Skill Mismatch Patterns in Europe: A Multivariate Statistical Approach. In C. Vasiliu, D.-C. Dabija, A. Tziner, D. Pleșea, & V. Dinu (Eds.), *Proceedings of BASIQ International Conference on New Trends in Sustainable Business and Consumption, 12th Edition* (pp. 618–625). Editura ASE.

DOI 10.24818/BASIQ/2026/12/041

Abstract

This paper aims to identify patterns of skill mismatch across European countries by adopting a multidimensional approach that integrates indicators of skill mismatch and educational mismatch. The study seeks to highlight structural differences between countries in terms of the alignment between skills, education, and labour market requirements. The analysis is based on Eurostat data for 2024 and includes indicators related to overqualification, underqualification, and the match between field of education and occupation. A Principal Component Analysis (PCA) is applied to reduce data dimensionality and identify latent dimensions of skill mismatch. Subsequently, hierarchical, and K-means cluster analyses are employed to group European countries into homogeneous clusters based on their skill mismatch profiles. The results reveal the existence of distinct patterns of skill mismatch across European countries. Three main dimensions are identified, reflecting educational-job alignment, the structure of educational fields, and work experience and field-specific differentiation. The cluster analysis highlights the presence of different groups of countries characterized by varying combinations of overqualification, underqualification, and educational mismatch, indicating that skill mismatch is not uniform across Europe but structurally differentiated. The paper contributes to the literature by proposing a multidimensional and comparative approach to skill mismatch, combining PCA and cluster analysis to identify country typologies. Unlike traditional studies focusing on single indicators, this research captures the complexity of the phenomenon and provides a more comprehensive perspective. The findings offer relevant insights for policymakers, suggesting that strategies to reduce skill mismatch should be tailored to the specific profiles of countries, taking into account structural differences in education systems and labour market dynamics.

Keywords

Skill mismatch, educational mismatch; principal component analysis; cluster analysis; labour market

DOI: 10.24818/BASIQ/2026/12/041

Introduction

In the context of rapid economic transformations driven by digitalisation, globalisation, and structural changes in labour markets, skill mismatch has become a central concern for both academic research and policymakers. Skill mismatch refers to the discrepancies between individuals' skills and job requirements and may have significant implications for productivity, competitiveness, and overall economic performance (McGuinness et al., 2018). The literature highlights the multidimensional nature of this phenomenon, emphasizing the coexistence of various forms of mismatch, such as overqualification, underqualification, and field-of-study mismatch (Montt, 2017). At the same time, empirical studies show that skill mismatch does not occur uniformly across countries but reflects structural differences related to education systems, labour market institutions, and the evolving demand for skills (Ghignoni & Verashchagina, 2014). As a result, some economies are characterised by high levels of overqualification, while others face skill

shortages or more complex, mixed forms of mismatch. In this context, a comparative analysis of skill mismatch patterns across countries becomes essential for understanding the underlying mechanisms driving these differences and for supporting the design of more effective public policies.

Building on these considerations, this paper aims to analyse skill mismatch across European countries from a multidimensional perspective, using indicators that capture both skill mismatches and the alignment between education and occupation. The proposed approach combines dimensionality reduction and classification techniques, enabling the identification of latent structures and country typologies with similar profiles. The main objective of the study is to identify patterns of skill mismatch at the level of European countries by applying a multidimensional framework based on Principal Component Analysis and cluster analysis. The paper stands out through its innovative approach, integrating multiple dimensions of the phenomenon, including overqualification, underqualification, and field-of-study mismatch. The use of Principal Component Analysis allows for the extraction of latent dimensions underlying skill mismatch, providing a synthetic view of the relationships among the selected indicators. Furthermore, the application of clustering techniques facilitates the identification of distinct groups of European countries, highlighting the existence of different structural patterns of mismatch. By relying on recent Eurostat data and incorporating the structural dimension of educational fields, this study contributes to the literature through a comparative and multidimensional analysis of skill mismatch.

The paper is structured into three main sections. The first section provides a review of the relevant literature, highlighting the key findings of previous studies on skill mismatch. The second section presents the data and methodology, including a description of the selected indicators and the analytical methods employed. The third section reports and discusses the empirical results, obtained through the application of Principal Component Analysis and clustering techniques. The final part of the paper summarizes the main conclusions of the study and outlines their implications.

1. Review of the scientific literature

The literature highlights that skill mismatch is a complex and multidimensional phenomenon for which no single measurement approach exists. The choice of indicators significantly influences empirical results, both in terms of the estimated incidence of the phenomenon and its effects on the labour market. In this context, empirical research has developed several distinct measurement approaches, each with its own advantages and limitations. Capturing the multiple facets of skill mismatch requires moving beyond traditional approaches based on human capital theory (Sala, 2011). McGuinness et al. (2018) show that the concept encompasses various forms of labour market frictions, including vertical mismatch, skill gaps, skill shortages, field-of-study mismatch, and discrepancies between individuals' actual skills and job requirements. These different forms of mismatch have distinct causes and consequences, which justifies their separate consideration in empirical analyses. In this context, the present study adopts a multidimensional approach to skill mismatch, combining several indicators—such as skills higher or lower than job requirements, field-of-education match, and overqualification—in order to provide a more comprehensive assessment of both the extent and the structure of the phenomenon.

The European Commission proposes a dual perspective on skill mismatch, distinguishing between a vertical and a horizontal dimension. The vertical dimension is typically captured through the overqualification rate, while the horizontal dimension is reflected by the match between the field of education and occupation. In this framework, a set of experimental indicators has been developed to capture the different facets of skill mismatch. Overqualification refers to individuals with tertiary education who are employed in jobs that do not require the knowledge and skills associated with their level of education. In turn, the “rate of skills mismatch by field of education” measures the discrepancy between the field in which an individual is employed and the field in which they obtained their highest level of education (Eurostat, 2026).

Some approaches to measuring skill mismatch rely on comparing an individual's level of education with the level required for their occupation, allowing for the identification of overqualification and underqualification. However, the use of education as a proxy for actual skills represents an important limitation, as mismatches between the field of study and the job can have significant effects both at the individual level and at the level of society as a whole (Groot & Maassen van den Brink, 2000; Somers et al., 2019).

Another strand of the literature relies on subjective measures of skill mismatch, based on individuals' self-assessment of how well their skills match job requirements. These measures have the advantage of directly capturing the relationship between skills and actual job tasks and have proven useful in explaining job satisfaction and occupational mobility. However, the literature also highlights that such evaluations may be

influenced by psychological and social factors, which can limit the comparability of results across individuals and contexts (Allen & van der Velden, 2001).

A more recent line of research focuses on the use of observed skills, measured through standardized assessments (such as PIAAC data). This approach enables a direct comparison between individuals' actual skill levels and the estimated skill requirements of different occupations. Empirical studies suggest that such measures are more closely aligned with the theoretical concept of skill mismatch; however, they require complex data and advanced methodological frameworks (Pellizzari & Fichen, 2017; Pérez Rodríguez et al., 2024). Recent literature highlights that the level of digitalisation of economies is closely linked to skill adequacy and innovation performance, suggesting that skills development represents a key mechanism through which digitalisation influences economic outcomes. Accordingly, a better alignment between skills and the demands generated by digitalisation contributes not only to increased employability, but also to improved innovation performance at the macroeconomic level (Rîndaşu et al., 2023). In this context, skill mismatch can be interpreted as a structural dysfunction that limits the effective utilisation of digital and innovative potential, as the misalignment between available skills and labour market requirements reduces the efficiency of this process.

At the same time, the literature highlights significant cross-country differences in the manifestation of skill mismatch, suggesting the existence of distinct patterns. Comparative studies show that, in European economies, mismatch is driven by both supply-side factors (such as the characteristics of education systems) and demand-side factors (including economic structure and technological change), leading to different configurations of the phenomenon across countries (Ghignoni & Verashchagina, 2014). Macroeconomic analyses further indicate the presence of diverse combinations of overqualification, underqualification, and skill shortages, reflecting the existence of distinct "mismatch regimes" (Vandeplas & Thum-Thysen, 2019). In addition, recent approaches based on the concept of skill formation regimes suggest that these patterns are shaped by labour market institutions and the interaction between education systems and the economy (González-Velosa et al., 2016). Other studies emphasize that temporal mismatches between graduates' skills and employers' needs, as well as the lack of transparency and cooperation between universities and the business sector, represent important drivers of skill mismatch, highlighting the crucial role of university-business collaboration in mitigating this phenomenon (Amicarelli et al., 2022).

In this context, the present paper adopts an integrated approach by combining multiple indicators that capture both skill mismatch and educational mismatch, and applies multivariate techniques to identify patterns across European countries.

2. Data and methodology

In order to capture the multiple facets of skill mismatch, the indicators included in the analysis are grouped into three main categories, according to the dimension of the phenomenon they reflect. First, skill mismatch indicators include variables that measure the relationship between individuals' skill levels and job requirements, capturing both overqualification and underqualification. Second, educational mismatch indicators reflect the degree of alignment between the field of education and the occupation, both at an aggregate level and across specific fields of study. Third, experience-related indicators capture the influence of work experience on the match between education and occupation, highlighting the importance of practical experience for labour market integration. Thus, the selected variables combines measures of vertical mismatch (overqualification and underqualification), horizontal mismatch (field-of-education mismatch), and indicators related to work experience during studies, allowing for a broader assessment of the relationship between education, skills, and labour market integration. In addition, specific educational fields such as ICT, engineering, business, health, and social sciences were included, as they reflect sectors with different levels of occupational specificity and labour market absorption, frequently associated in the literature with distinct patterns of educational-job alignment and skill mismatch. The values of the selected indicators were obtained from the Eurostat database and refer to 29 European countries (EU and non-EU), for the year 2024 (the most recent available year), and are expressed as percentages. The full list of indicators used in the analysis is presented in the following table no.1.

Table no. 1. Description of statistical indicators included in the analysis

Name of statistical variable	Code/Link
Persons not in formal education by match between skills and current/last main job, aged 15-34 (Skills higher than job requirements, Skills lower than job requirements) (%)	Eurostat Online code: lfso_24match13 https://doi.org/10.2908/LFSO_24MATCH13

Persons by match between field of education and current/last main job and field of education, aged 15-34 (Very high or high match / No match – Total/ Social sciences, journalism, and information / Business, administration/ Information and communication technologies/ Engineering, manufacturing, and construction/ Health and welfare) (%)	Eurostat Online code: lfso_24match06 https://doi.org/10.2908/LFSO_24MATCH06
Persons by match between field of education and current/last main job and work experience while studying (15-34) (at least 1 month work experience / No work experience or less than 1 month) (%)	Eurostat Online code: lfso_24match05 https://doi.org/10.2908/LFSO_24MATCH05
Over-qualification rates by economic activity (%)	Eurostat Online code: lfso_eoqgan2 https://doi.org/10.2908/LFSO_EOQGAN2

Source: Authors' own selection.

In order to identify patterns of skill mismatch across European countries, the empirical analysis was conducted in several complementary stages. In the first stage, a descriptive analysis of the selected indicators was performed. In the second stage, Principal Component Analysis (PCA) was applied to reduce data dimensionality and to identify the latent structures underlying the phenomenon. In the third stage, cluster analysis was conducted based on the component scores, with the aim of grouping countries into homogeneous typologies from the perspective of skill mismatch. The combination of these methods enabled an integrated approach, facilitating both a multidimensional interpretation of the phenomenon and the identification of structural differences across European countries.

The descriptive analysis highlights the distribution of the indicators used to characterize skill mismatch across European countries, providing insights into central tendency, variability, and the shape of the distributions.

Principal Component Analysis (PCA) was applied in order to identify the latent dimensions structuring the differences between European countries in terms of skill mismatch. The set of variables captures multiple facets of the phenomenon, including the mismatch between individuals' skills and job requirements, the misalignment between field of study and occupation, and overqualification. In this context, PCA pursued three main objectives. First, it aimed to reduce the dimensionality of the dataset. Given the inclusion of multiple correlated variables, PCA allows the information to be summarized into a smaller number of components without significant loss of information. Second, it sought to identify the internal structure of the skill mismatch phenomenon by revealing whether the indicators cluster around interpretable dimensions, such as educational-job alignment, the specificity of certain fields of study, or the imbalance between overqualification and underqualification. Third, it served as a preparatory step for the cluster analysis, as the extracted components can be used as synthetic variables for grouping European countries into relatively homogeneous typologies based on skill mismatch patterns.

Cluster analysis was subsequently employed to identify homogeneous groups of European countries according to the patterns of skill mismatch previously revealed by PCA. The main objective of this method was to construct a typology of countries based on synthetic dimensions reflecting the degree of alignment between education and occupation, the structure of educational fields, and the imbalance between overqualification and underqualification. The use of component scores instead of the original variables offers several advantages, including reduced data dimensionality, elimination of multicollinearity, and a clearer interpretation of the resulting clusters.

3. Results and discussion

The descriptive analysis of the variables reveals the existence of educational fields with higher variability across countries in terms of a high or very high level of match between the field of study and the job domain, particularly in ICT and social sciences. Similarly, greater cross-country differences are observed for individuals with significant work experience acquired during their education period. In contrast, underqualification appears to be more evenly distributed across countries, with relatively smaller differences. Spain and Greece exhibit particularly high values of overqualification compared to other European countries, while Luxembourg stands out with very low levels of this indicator. For most variables, the distributions show low to moderate positive skewness, indicating a predominance of countries with lower values of the indicators. Additionally, in the case of most variables, the kurtosis coefficient is negative, reflecting flatter distributions and a higher degree of variability across countries.

The PCA results indicate that the model is suitable for the application of Principal Component Analysis. The value of the Kaiser-Meyer-Olkin (KMO) measure is close to 0.8 (KMO = 0.793), suggesting a good

level of sampling adequacy, as the variables exhibit sufficient shared correlations to allow for the extraction of stable and interpretable components. In addition, Bartlett's test of sphericity is statistically significant (Chi-Square = 192.807; df = 66; Sig. = 0.000), indicating that the correlation matrix significantly differs from an identity matrix. This confirms that the variables are sufficiently intercorrelated and that the use of PCA is appropriate (Table no. 2).

As a result of the analysis, three principal components were retained, all with eigenvalues greater than 1. Together, these components explain 67.94% of the total variance. Following Varimax rotation, the distribution of explained variance across the three components is as follows: Component 1 accounts for 34.119%, Component 2 for 20.952%, and Component 3 for 12.867% (Table no. 3; Figure no. 1).

Table no. 2. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.793
Bartlett's Test of Sphericity	Approx. Chi-Square	192.807
	df	66
	Sig.	.000

Table no. 3. Total Variance Explained (first three components)

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.582	46.514	46.514	4.094	34.119	34.119
2	1.537	12.808	59.323	2.514	20.952	55.071
3	1.034	8.615	67.938	1.544	12.867	67.938

Source: Own contribution, based on Eurostat data.

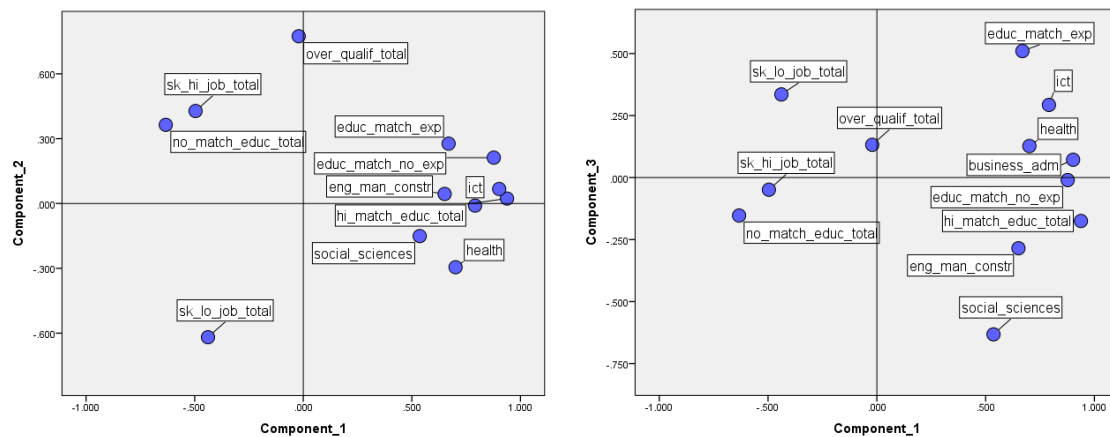


Figure no. 1. Component Plot in Rotated Space

Source: Own contribution, based on Eurostat data.

The principal component analysis reveals three distinct dimensions underlying the relationship between education and occupation across countries. Component 1 - *Education-Job Alignment* - captures the overall degree of alignment between individuals' educational attainment and their occupations. Positive values are associated with higher levels of educational match, both among individuals with and without prior work experience, as well as with a stronger concentration in fields such as ICT, business administration, and health, where the link between education and occupation is typically more direct. In contrast, negative values are associated with higher levels of mismatch, including both underqualification and overqualification. This component can therefore be interpreted as a continuum ranging from weak alignment to strong education-job correspondence in the labour market. Component 2 - *Educational Structure and Overqualification* - reflects structural differences across countries in the way education translates into labour market outcomes, with a strong contribution from overqualification. Higher scores on this dimension are associated with a greater prevalence of overqualification alongside moderate levels of educational matching, suggesting labour markets where individuals' qualifications exceed job requirements despite a certain degree of structural organization. At the same time, this component captures variation related to fields of study, indicating that the extent of matching is influenced by the structural composition of education systems and their alignment with labour market demand. Component 3 - *Experience and Field-Specific Differentiation* - highlights differences related to the role of work experience and field-specific employment patterns. Positive values are associated with stronger educational matching among individuals with prior work experience and with fields such as ICT, health, and business. Negative values, in turn, are linked to fields such as social sciences and engineering, where the transition from education to employment may be less direct or more heterogeneous. This component suggests that both work experience and field of study play an important role in shaping the effectiveness of education-job matching across countries.

Taken together, the three components suggest that skill mismatch in Europe is shaped not only by the overall degree of education–job alignment, but also by structural differences in educational systems, labour market absorption capacity, and the role of work experience in facilitating labour market integration. The results indicate that countries differ both in the intensity and in the configuration of mismatch patterns, supporting the idea that skill mismatch should be interpreted as a multidimensional and structurally embedded phenomenon rather than as a single labour market imbalance.

Two clustering methods (Ward’s hierarchical method and k-means) were employed to build on the results of the principal component analysis, grouping countries according to their positions along three underlying dimensions: education–job alignment, structural characteristics, and experience-related matching. This integrated approach allows for a more comprehensive assessment of cross-country differences, facilitating the identification of broader and more meaningful patterns that extend beyond individual indicators.

Three clusters of countries can be distinguished (Figures no. 2, 3, Table 4). Cluster 1 (IT, SK, DK, NL, PL, SE, EE) includes countries characterized by lower levels of education–job alignment and a higher incidence of mismatch. These labour markets tend to display weaker links between educational attainment and occupational outcomes, suggesting less efficient school-to-work transitions and a greater prevalence of both overqualification and underqualification. In addition, the relatively low scores on the experience-related dimension indicate that work experience plays a more limited role in improving matching outcomes. Cluster 2 (FR, CZ, HR, BG, PT, AT, CY, ES, EL, BE, NO, LU, FI, RO, MT) represents a group of countries with intermediate and heterogeneous profiles. These countries are generally positioned around the center of the alignment dimension, indicating moderate levels of match between education and jobs. However, they exhibit significant variation in terms of structural characteristics, particularly with respect to overqualification and the distribution of employment across fields of study. This cluster reflects mixed or transitional labour market systems, where both alignment and mismatch coexist and where structural factors play an important but uneven role. Cluster 3 (DE, LT, LV, HU, SI) comprises countries with higher levels of education–job alignment and stronger integration between education systems and labour markets. These countries tend to exhibit more effective matching mechanisms, supported by clearer links between fields of study and occupations, as well as a stronger role of work experience in facilitating employment outcomes. Overall, this cluster reflects more efficient and better-coordinated labour market systems. Overall, the results highlight the coexistence of distinct labour market regimes across Europe, ranging from mismatch-prone systems to more efficient and well-aligned structures. This diversity suggests that educational mismatch is shaped by country-specific institutional arrangements, labour market structures, and the degree to which education systems are aligned with economic demand.

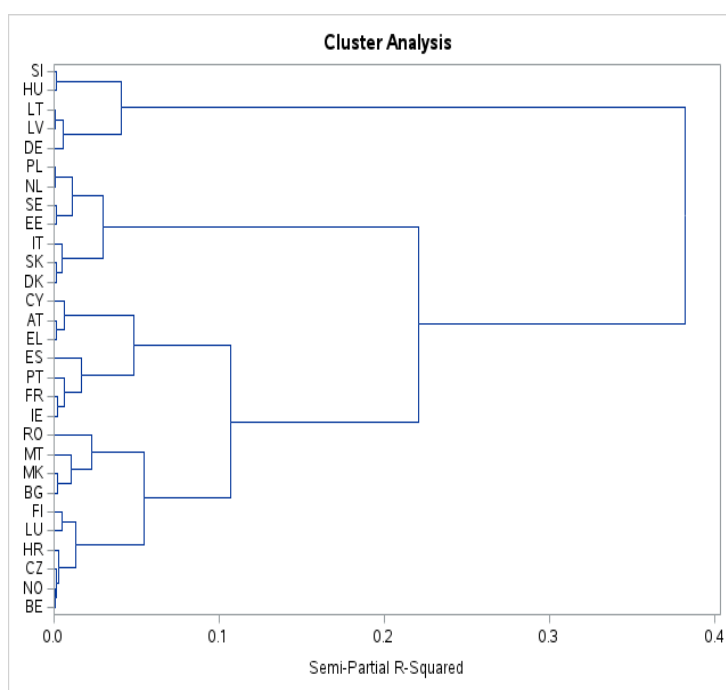


Figure no. 2. Dendrogram
Source: Own contribution, based on Eurostat data

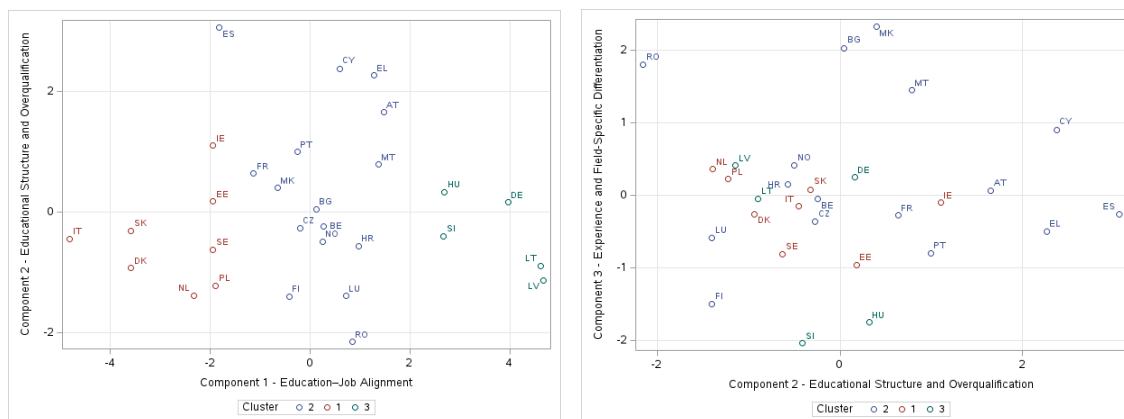


Figure no. 3. Projection of countries onto the principal component planes

Source: Own contribution, based on Eurostat data.

Table no. 4. Final Cluster Centers

Cluster Means			
Cluster	Component 1	Component 2	Component 3
1	-2.756184710	-0.460576658	-0.201780237
2	0.213731790	0.353632573	0.299182103
3	3.725953807	-0.394701583	-0.634534349

Source: Own contribution, based on Eurostat data

Conclusions

The analysis highlights clear cross-country differences in education–job alignment, with three distinct patterns emerging from the data. Some countries show a strong alignment between education and jobs, supported by clearer links between fields of study and occupations and by the effective role of work experience in easing the transition into employment. At the other end, there are countries where both overqualification and underqualification are more common, suggesting that skills are not being used efficiently. Between these two, a third group reflects more mixed situations, where moderate levels of alignment coexist with structural imbalances, especially in relation to overqualification and field-specific matching.

These findings suggest that educational mismatch is not only about how much education people have, but also about how well education systems are connected to labour market demand. In particular, the results highlight the importance of field-specific pathways and work-based learning in improving the match between education and employment.

From a policy perspective, this means that a one-size-fits-all approach is unlikely to be effective. For countries included in the overqualification-driven economies cluster, the results indicate the need for policies aimed at improving the utilisation of human capital and strengthening the alignment between higher education output and labour market demand. Measures could include stronger cooperation between universities and employers, career guidance systems, and policies supporting the transition of highly educated individuals into occupations matching their qualifications. In the case of the underqualification / skill shortage economies cluster, the findings highlight the importance of policies focused on upskilling and reskilling, particularly in sectors facing labour shortages. Lifelong learning programmes, vocational training, and investments in digital and technical skills may contribute to reducing skill deficits and improving labour market adaptability. For the structurally distinct mismatch economies, the results suggest the need for more targeted and flexible policy interventions, taking into account the heterogeneous nature of mismatch patterns. In these countries, policies promoting stronger links between education systems and labour market needs, as well as better monitoring of emerging skill demands, may be particularly relevant.

At the same time, the results should be interpreted with some caution, as the analysis is based on aggregated data and on a normative mapping between education and occupations, which may not fully capture the complexity of skill requirements. Also, the analysis relies on cross-sectional data for a single year (2024), which limits the possibility of capturing the dynamic evolution of skill mismatch patterns over time. Future

research could build on these findings by using micro-level data and by exploring additional aspects such as wages, job quality, or sectoral differences, from a longitudinal perspective, in order to better understand how mismatch affects labour market outcomes over time.

Generative Artificial Intelligence (GenAI) usage statement:

No GenAI tool was used in the development of this paper.

References

- Allen, J., & van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers*, 53(3), 434–452, <https://doi.org/10.1093/oep/53.3.434>.
- Amicarelli, V., Miuli, G., Bux, C., & Grosu, R.M. (2022). Advancing University-Business Cooperation in the Mediterranean Area. *Amfiteatru Economic*, 24(61), 832–846, <https://doi.org/10.24818/EA/2022/61/832>.
- Eurostat. (n.d.). *Skills mismatch experimental indicators. Methodological note. Eurostat Directorate F: Social statistics, Unit F1: Social indicators; methodology and development; Relations with users*. Retrieved April 14, 2026 from <http://ec.europa.eu/eurostat>.
- Ghignoni, E., & Verashchagina, A. (2014). Educational qualifications mismatch in Europe. Is it demand or supply driven? *Journal of Comparative Economics*, 42(3), 670–692, <https://doi.org/10.1016/j.jce.2013.06.006>.
- González-Velosa, C., Rosas, D., & Flores, R. (2016). On-the-job training in latin america and the caribbean: Recent evidence. In Inter-American Development Bank, M. Grazzi, & C. Pietrobelli (Ed.), *Firm Innovation and Productivity in Latin America and the Caribbean* (pp. 137–166). Palgrave Macmillan US. https://doi.org/10.1057/978-1-349-58151-1_5.
- Groot, W., & Maassen van den Brink, H. (2000). Overeducation in the labor market: A meta-analysis. *Economics of Education Review*, 19(2), 149–158, [https://doi.org/10.1016/S0272-7757\(99\)00057-6](https://doi.org/10.1016/S0272-7757(99)00057-6).
- McGuinness, S., Pouliakas, K. & Redmond, P. (2018). Skills mismatch: concepts, measurement and policy approaches. *Journal of Economic Surveys*, 32: 985–1015, <https://doi.org/10.1111/joes.12254>.
- Montt, G. (2017). Field-of-study mismatch and overqualification: Labour market correlates and their wage penalty. *IZA Journal of Labor Economics*, 6(1), 10.1186/s40172-016-0052-x.
- Pellizzari, M., & Fichen, A. (2017). A new measure of skills mismatch: Theory and evidence from PIAAC. *IZA Journal of Labor Economics*, 6(1), <https://doi.org/10.1186/s40172-016-0051-y>.
- Pérez Rodríguez, S., van der Velden, R., Huijts, T., & Jacobs, B. (2024). Identifying literacy and numeracy skill mismatch in OECD countries using the job analysis method, *Oxford Economic Papers*, 76(3), 859–876, <https://doi.org/10.1093/oep/gpad045>.
- Rîndașu, S.M., Ionescu-Feleagă, L., Ionescu, B.S., & Topor, I.D. (2023). Digitalisation and Skills Adequacy as Determinants of Innovation for Sustainable Development in EU Countries: A PLS-SEM Approach. *Amfiteatru Economic*, 25(Special Issue 17), 968–986, 10.24818/EA/2023/S17/968.
- Sala, G. (2011). Approaches to skills mismatch in the labour market: A literature review. *Papers: Revista de Sociologia*, 96(4), 1025–1045. <https://ddd.uab.cat/record/79022>.
- Somers, M.A., Cabus, S.J., Groot, W., & Maassen van den Brink, H. (2019). Horizontal Mismatch Between Employment And Field Of Education: Evidence From A Systematic Literature Review, *Journal of Economic Surveys*, 33(2), 567–603, <https://doi.org/10.1111/joes.122>.
- Vandeplas, A., & Thum-Thysen, A. (2019). *Skills Mismatch and Productivity in the EU. European Economy - Discussion Papers 100, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission*. Retrieved April 14, 2026 from https://economy-finance.ec.europa.eu/publications/skills-mismatch-and-productivity-eu_en.