PILLARS – Pathways to Inclusive Labour Markets: Methodological note on the identification of good policy practices in Europe

Part of Deliverable 7.4

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1 Introduction

The current document represents a methodological note on the **identification of good practices of inclusive labour market policies in Europe**, aimed to increase resilience and inclusiveness of the labour market during automation technology-driven transformation. This note is based on the PILLARS Deliverable 7.4 – the report on good practices of existing policies. The report discussed findings at **two levels**: at the level of **policy approaches/strategies** and at the level of **policy instruments** that underpin these approaches/strategies.

The unit of analysis was **NUTS 2 regions**, defined by Eurostat. The report produced **10 regional case studies**, examined success factors and barriers of selected regions, accounting for contextual factors. By focusing on 10 selected regions across several tasks, the project team was able to explore these regions in depth. The case studies have been conducted in 2022-2023. They have been developed based on a literature review and interviews with the following stakeholders - policymakers, academic experts, industry and civil society representatives. Combined findings have been discussed and validated during the PILLARS ESG meetings and a stakeholder workshop in Brussels in June 2023.

The findings contributed to answering the question: **What set of policies can ensure preparedness for an inclusive labour market, while capitalising on the opportunities created by automation technologies?** Thus, the three policy goals have been in the focus of the analysis:

- **Stimulate creation of innovative and inclusive jobs**, powered by automation technologies;
- **Prevent and mitigate job displacement**, following adoption of automation technologies; and
- **Support employers and employees during job transformation**, following adoption of automation technologies.

In the report, technological transformation referred to automation technology adoption, given that policies associated with technological transformation incorporate automation technologies. Therefore, these terms have been used interchangeably.

2 Methodology

The current chapter is organised in two sections. The first section focuses on the process of selection of regions for the case studies. It elaborates on the process of filtering/dismissing regions that have a lower potential for illustrating good practices. The second section of the chapter presents how data collection and analysis were conducted for each case study.

2.1 Selection of regions

Step 1: Definition of a composite indicator for measuring labour market performance

The first criteria in the selection of 10 regions that serve all above-listed purposes is to ensure that they include some **good practices** in the transition towards inclusive labour markets. Thus, selected regions should exhibit improving performance on relevant employment-related indications. As a reminder, the adoption of automation technologies/innovation may have **three effects on the labour market**: job displacement, job creation and job transformation.[1] Given an additional dimension of inclusion, good performance implies **reducing unemployment (quantity of work)** - job displacement, including among vulnerable groups, **increasing innovative and inclusive job creation (type and quantity of work)**, and **improving the quality of employment** – job transformation, following adoption of automation technologies.

Box 1 Definitions of job displacement, job creation and job transformation effects

- **Job displacement** refers to involuntary job loss and redundancies for employees, following eliminations of tasks or of types of jobs.
- **Job transformation** implies a change in the nature of work and of the workplace itself.
- **Innovation job creation** refers to the process of creation of new jobs due to adoption of automation technologies.
- **Inclusive job creation** refers to the process of creation of new jobs that stimulate inclusion, especially for people who were previously unemployed or inactive on the labour market.

Source: Pillars (2022)

For this purpose, it is critical to develop/identify a composite indicator that captures performance in the above-listed measures at NUTS2 level. Moreover, OECD (2020) stresses that an inclusive economic growth should capture not only a rate (good performance) but also a **direction towards greater inclusion**.[2] Thus, there should be evidence of improving labour market performance **over time**. After testing multiple options from data sources and

[1] https://www.oecd.org/els/the-impact-of-ai-on-the-workplace-evidence-from-oecd-case-studies-of-ai-implementation-2247ce58-en.htm

[2] https://www.oecd-ilibrary.org/urban-rural-and-regional-development/broad-based-innovation-policy-for-all-regions-and-cities_299731d2-en

recognising data limitations, the Pillars WP7 team decided to use the composite indicator from the **Regional Competitiveness Index (RCI)** that focuses on **labour market efficiency**. Table 1 illustrates how indicators from this group relate to the three labour market effects in focus. Overall, they seem to serve the intended purpose, although a greater availability of relevant indicators would produce more robust estimates.

Table 1 Selected indicators from RCI on labour market efficiency

Effect on the labour market	Potential evidence of good practices	Indicator from the RCI	Short description of the indicator
Job displacement	Decreasing unemployment rate overall and among potentially vulnerable groups (e.g., women, youth)	Unemployment	Percentage of active population
		Long-term unemployment rate	Percentage of labour force unemployed for 12 months or more
		Gender balance unemployment	Distance to equilibrium: absolute value of (rate women - rate men)
		Gender balance employment	Distance to equilibrium: absolute value of (rate women - rate men)
		Female unemployment	Percentage of female unemployed
		NEET	Share of population aged 15-24 not in education, employment, training
Innovative and inclusive job creation	Increasing employment in more knowledge intensive industries/organisations, including for potentially vulnerable groups	Employment rate (no agriculture)	Persons employed aged 15-64 (excl. agriculture) as % of population same age cohort
Job transformation	Improving employment/working conditions	Involuntary part-time/temporary employment	Share of population aged 20-64 in involuntary part-time or temporary job
	Increasing productivity at work (e.g., due to training or lower number of working hours)	Labour productivity	GDP/hours worked (EU28=100)

Pillars (2023), based on RCI

The use of the RCI has several advantages. First, the data is **available for 2019** (that captures average values in 2015-2017) and **for 2013** (that captures average values in 2009-2011). This allows to observe a change in labour/employment-related indicators between 2009 and 2017, and this is the most recent data available at NUTS2 level for these indicators. Second, the RCI composite indicator on labour market efficiency uses a rigorous methodology for **normalising data across relevant indicators and provides an overall score relative to the EU mean**. Thus, the data is displayed as a score of the standard deviation from the EU mean. It allows to compare performance of regions across time, relative to other EU countries and relative to the EU mean. However, it does not display data in absolute values, which prevents analysis against own performance in previous periods.

The available indicators on **job displacement** are suitable for capturing the overall change in employment and a change in employment of women and youth. The availability of (proxy) indicators on **innovative and inclusive job creation** is very limited at NUTS2 level, especially across time. Data on inclusive job creation has not been found in any publicly available databases. Thus, an indicator on change in employment outside the agriculture sector serves as a relatively suitable proxy that highlights a quantity of more knowledge-intensive/innovative jobs.

The data on **job transformation** is also challenging to capture, as it includes multiple dimensions that require qualitative assessment of job quality, working and employment conditions, industrial relations etc. Nevertheless, the two RCI indicators (involuntary part-time/temporary employment and labour productivity) serve as proxies for changing employment/working conditions. It is important to point out that RCI did not include an indicator "involuntary part-time/temporary employment" in 2013, therefore a composite indicator on labour market efficiency in 2019 better serves the purpose of measuring job transformation.

The main complexities with using the RCI data are associated with changes in NUTS2 classification between 2013 and 2019. Such changes are particularly difficult to tackle in regions that have been divided or have had their borders redefined. In these cases, is not possible to compare RCI/labour productivity scores before and after the reclassification. Therefore, regions which have been divided between 2013 and 2019 were dismissed as potential case studies.

Step 2: Verification of a trade-off between inclusion and innovation

OECD (2019) points out that regions face a **trade-off between economic growth and inclusion**.[3] This implies that an increase in relevant labour market indicators should not occur at the expense of technological transformation, efficiency or vice versa. The model that has been presented in Deliverable 7.3 illustrated a two-fold ambition/direction of regions/countries towards high innovativeness of the economy and high performance on employment-related indicators (Figure 1, top-right quadrant). In view of this, it is necessary to check the performance of pre-selected regions **against indicators of innovativeness of the economy** (as we use innovation as a proxy for technological transformation). A preferred case is when a region has a high positive change on both labour market and innovation indicators.

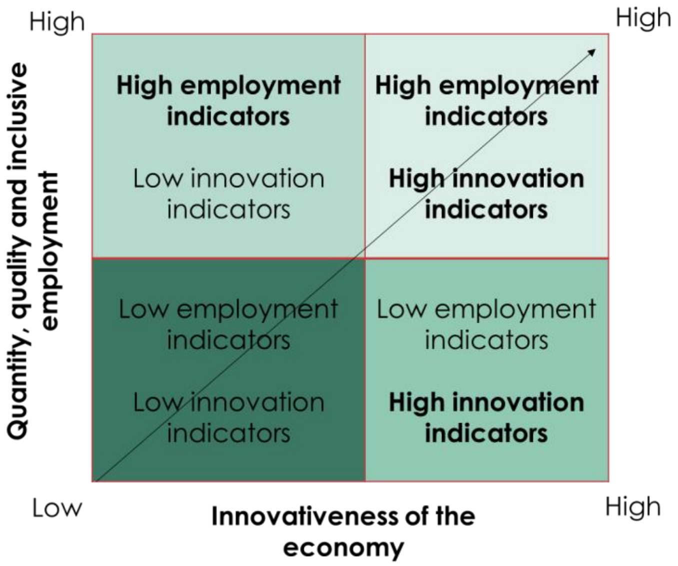
To measure regional innovativeness, the Pillars WP7 team uses the **Regional Innovation Scoreboard** (RIS). RIS provides a comparative and comprehensive assessment of the innovation performance at NUTS2 level, incorporating 21 sub-indicators that are aligned with the Pillars policy areas. For example, RIS indicators on **innovation and industry** include R&D expenditure in the public sector, PCT patent applications, sales of new-to-market and new-to-firm innovations; RIS indicators on **education and training** include population with tertiary education, lifelong learning, digital skills. To some extent, RIS could serve as a proxy indicator for current or potential innovative job creation, as innovation stimulates employment in

[3] https://www.oecd.org/cfe/regions-in-industrial-transition-c76ec2a1-en.htm

innovative industries/organisations. Thus, it may compensate for a lack of indicators of the RCI on innovative job creation.

Other reasons for using RIS include – availability of data for a similar time period as RCI, namely 2014-2021, and a similar methodology as RCI. The latter implies that the data is also normalized across indicators and calculated as a deviation from the EU mean. Lastly, RIS provides a typology of regions that is useful for future analysis (this is discussed in detail below).

Figure 1 A simplified model of the two-fold ambitions of policymakers



Source: Pillars (2022)

Step 3: Pre-selection of regions

The process of pre-selection of regions represents the filtering of regions with a lower potential for illustrating good practices.

First, based on 2013-2019 RCI data, the Pillars WP7 team derived the difference change in the labour market performance score in each region. The team pre-selected regions that have had a positive (above 0) change within this period, implying that these are regions that have improved in some, or in all, employment-related indicators. A faster convergence (to the EU mean) in performance could suggest that a region has applied specific measures/policies that proved to be effective. Regions with negative change in performance have been dismissed from further selection.

Second, the Pillars WP7 team assessed the **innovation performance of the pre-selected regions** using RIS data of 2014 and 2021. Similarly, the difference in innovation performance was calculated to grasp how the region is evolving along the innovation track. Regions that improved their innovation index (in relation to their performance in 2014) were selected to move to the next phase. As mentioned earlier, a preferred case is when a region has significantly improved its innovation performance, although if region's innovation performance remained stable it has not been dismissed. Given that the RIS EU mean has increased by 15% since 2014, only the regions whose innovation performance in 2019 has declined by more than 15% relative to own performance in 2014 have been removed from further pre-selection.

Step 3: Final selection of cases according to the regional typology and criteria on diversity

From the final pool of regions, it was necessary to select different types of regions to ensure diversity. In general, there is a large variety of typologies for regions, based on a degree of urbanisation, GDP per capita, industrial specialisation, population size etc. Although, most typologies are applied only at NUTS3 level, as a higher level of aggregation dilutes local differences. The critical factor in the selection of a typology is its utility for the analysis. Given that the Pillars WP7 discusses inclusive labour market in the context of technological transformation/innovation, it is critical to differentiate between **different types of innovators**.

The typologies of innovators also vary, according to the type of regional innovation systems, networks, technologies etc. Nevertheless, most discussions on "inclusive innovation policies" and innovation in different types of regions centres on the **levels of innovativeness of regions**. For examples, OECD (2020) positions regions between two extreme cases: the so-called "frontier regions" characterised as most developed in terms of science, technology and innovation, and regions lagging behind the technological frontier.[4] The first category of regions typically has higher levels of GDP per capita and of overall development. Similarly, Ahlin, Drnovsek and Hisrich (2014) classify regions, based on absorptive capacities of their innovation systems that is linked to investment in research and development (R&D).[5] The guide to Research and Innovation Strategies for Smart Specialisations (2012) also distinguishes between three types of regions (knowledge hubs, industrial production zones, non-science and technology regional system), based on their knowledge intensity. In view of that, **RIS clusters regions in 4 groups**, according to their innovation performance relative to the EU average:

- Innovation leader (125%-160% of the EU average)
- Strong innovation (100%-124% of the EU average)
- Moderate innovator (70%-99% of the EU average)

[4] https://www.oecd-ilibrary.org/urban-rural-and-regional-development/broad-based-innovation-policy-for-all-regions-and-cities_299731d2-en

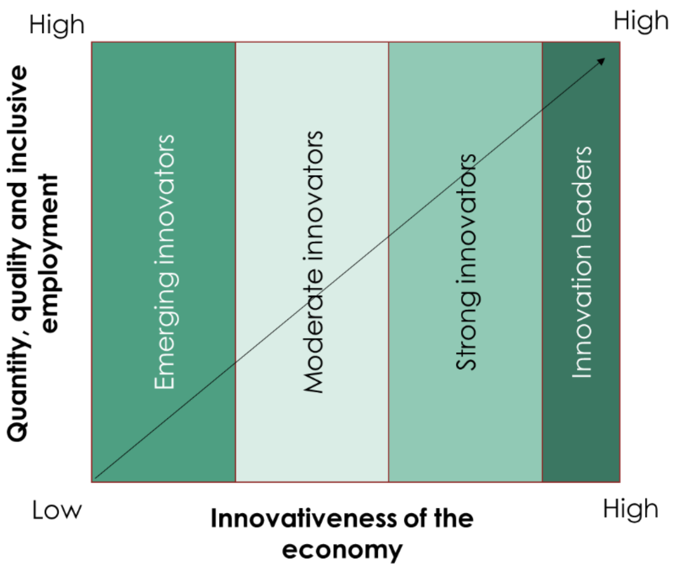
[5] https://www.jstor.org/stable/24330972

- Emerging innovator (0%-69% of the EU average)

Such typology allows to examine regions at different stages of innovation, with different innovation capabilities and resources allocated towards innovation and technological transformation. By dividing regions into these 4 groups and analysing performance within and between them, it is possible to provide **useful lessons for a specific group of regions** and **improving transferability of good practices within that group**. This is illustrated in Figure 2; the size of innovation groups depicted is proportional to the share of regions in these groups, highlighting that the number of innovation leaders comprises only 15% of all regions in the EU.

By combining multiple indicators — such as public and private expenditure in R&D, patent applications or innovating start-ups — RIS typology is a good instrument to estimate regional exposure to technological transformation, particularly to automation technologies. In the absence of data of regional labour markets exposure to emerging automation technologies at NUTS 2 level, one can assume that, i.e., emerging innovators face low exposure to automation, and innovation leaders face high exposure to automation. Different levels of exposure might require different sets of policies towards inclusive labour markets.

Figure 2 Four types of innovators, according to RIS, and their labour market performance



Source: Pillars (2022)

Once regions have been clustered into 4 RIS groups, the final selection has been performed within each group. It combined two objectives: first, to select best performers in terms of labour market indicators, and second, to ensure variety among the selected regions. The identification of best performers focused on both RCI score in 2019 and on a RCI change between 2013 and 2019, although a preference has been given to regions with a higher change in RCI scores.

The **process of selection** started by the “innovation leader” group (based on categorisation introduced in 2021), and then proceeded to the remaining groups, sorted by innovativeness level. Once a country had a region selected in one group, all regions of the same country were discarded as potential case studies.

For “emerging innovators” group that is characterised by low levels of innovativeness and therefore is likely to have low levels of exposure/presence of automation technologies, the preference has been given to regions with higher levels of innovativeness. Nevertheless, for a sake of variety, we have included one NUTS2 region that represents regions with an average level of innovation among the “emerging innovators” group, but which has a significant improvement on labour market related indicators in 2013-2019.

As mentioned earlier, the selected regions should not only illustrate best practices, but also serve as “archetypes” of other regions (Task 7.1.) to ensure variation in underlying factors. In view of this, and to wrap up what was described above, the selection of case studies was based on the following criteria: **geographic location/country and region in Europe, balance in terms of RIS innovation groups**. Moreover, the final selection should **respect heterogeneity in terms of levels of regional development, availability of highly skilled labour, migration pattern, population density** (Table 2).

The final selection of ten regions is presented in Table 3. Selected regions fully comply with the selection criteria, as illustrated in Table 4.

Table 2 Regional selection criteria and justification

Selection criteria	Justification
1 region per country (with preference of consortium partner countries)	Ensures diversity in contextual factors
Regions from all parts of Europe (Northern, Western, Eastern, Southern)	Essential for representativeness across the EU
1 region - “innovation leaders”, 3 regions – “strong innovators”, “moderate innovators”, “emerging innovators”	The selection of regions for examination should be proportional to the total share of regions in each innovation group in Europe (based on RIS 2021 data, it is 30% for each group, except “innovation leaders” – 15%)
Different levels of regional development, measured as GDP per capita in 2013 and 2021	Indicates availability of resources in a region. Eurostat differentiates regions based on their GDP (PPS) per capita in comparison to the EU average, at NUTS2 level: less developed regions (less than 75% of EU average), transition regions (between 75% and 90% of EU average), more developed regions (over 90% of EU average).
At least 4 regions with below EU average rate of people with tertiary education in 2013, and evidence of progression in 2021	Indicates availability of highly skilled labour and progression in time
Diversity in rates of net migration (2013-2020)	Indicates migration flows/attractiveness of a country and its labour resources in a period of time
At least 4 regions with below EU average population density	Diversity in terms of higher and lowers levels of urbanisation, which is associated with spatial distribution of resources, networks etc.

Pillars (2023)

Table 3 Selected regions and their performance, based on RIS and RCI

Name of the region (NUTS2 code)	Country (region in Europe)	Innovation performance group, based on RIS (2021)	RIS score 2021	Significant improvement in the following RIS indicators (between 2014 and 2021)	RCI score 2019	Change in RCI score (between 2013 and 2019)	Significant improvement in the following RCI indicators (between 2013 and 2019)
Köln (DEA2)	Germany (Western Europe)	Innovation leader	129.7	• Interna-tional scientific co-publications; • Business process innovators; • Trademark applications; • Sales of new-to-market and new-to-firm innovations	0.77	0.28	• Labour Productivity
Nordjylland (DK05)	Denmark (Northern Europe)	Strong innovator	116.9	• Interna-tional scientific co-publications; • Product process innovators; • Business process innovators; • Innovative SMEs collaborating with others	0.70	0.01	• Unemployment
Prague (CZ01)	Czech Republic (Eastern Europe)	Strong innovator	107.5	• Innovation expenditures per person employed; • Business process innovators; • Public-private co-publications; • Employment knowledge-intensive activities	0.64	0.17	• Labour Productivity
Estonia (EE00)	Estonia (Northern Europe)	Strong innovator	114.0	• Product process innovators; • Business process innovators; • Innovative SMEs collaborating with others; • Public-private co-publications	0.37	0.67	• Long Term Unemployment; • Unemployment; • Female unemployment; • NEET
Pays de la Loire	France (Western Europe)	Moderate innovator	99.2	• IT specialists; • Product process innovators; • Design applications;	0.29	0.09	• Employment rate

				• Employment knowledge-intensive activities			
Malta (MT00)	Malta (Southern Europe)	Moderate innovator	90.4	• Population with tertiary education; • Lifelong learning; • Most-cited publications; • IT specialists	0.06	0.46	• Employment rate; • Labour productivity
Lisbon (PT17)	Portugal (Southern Europe)	Moderate innovator	89.7	• Interna-tional scientific co-publications; • IT specialists; • Trademark applications; • Employment knowledge-inten-sive activities	0.03	0.23	• Labour productivity; • Gender balance employment
Dolnoslaskie (PL51)	Poland (Eastern Europe)	Emerging innovator	64.5	• Population with tertiary education; • Digital skills; • R&D expenditures business sector; • IT specialists	0.01	0.20	• Labour productivity
Közép-Dunántúl (HU21)	Hungary (Eastern Europe)	Emerging innovator	57.7	• R&D expenditures business sector; • Product process innovators; • Innovative SMEs collaborating with others; • Employment knowledge-intensive activities	0.31	0.59	• Employment rate; • Unemployment; • Labour productivity; • Female unemployment
Latvia (LV00)	Latvia (Northern Europe)	Emerging innovator	49.6	• Interna-tional scientific co-publications; • IT specialists; • Trademark applications; • Employment knowledge-inten-sive activities	-0.11	0.65	• Long-term unemployment; • Unemployment; • Female unemployment; • NEET

Pillars (2023), based on RIS and RCI data

Table 4 Data on selected regions, in line with the selection criteria

Name of the region (NUTS2 code)	GDP per inhabitant in PPS (% of EU-27 avg. from 2020 average) in 2013; (Level of development)	GDP per inhabitant in PPS (% of EU-27 avg. from 2020 average) in 2021; (Level of development)	Unemployment rate in 2013, (% labour force aged 15-74)[6]	Unemployment rate in 2021, (% labour force aged 15-74)[7]	Change in unemployment rate between 2013 and 2021, (% labour force, aged 15-74)	Tertiary education attainment (ages of 30-34), 2013[8]	Tertiary education attainment (ages of 30-34), 2021[9]	Change in tertiary education attainment (ages of 30-34) between 2013 and 2021	Total population in 2021	Average crude rate of net migration plus statistical adjustment (2013-2020)	Population density (persons per square km)[10], 2021
Köln (DEA2)	132% (More developed region)	124% (More developed region)	5.80%	4.0%	-1.8%	34.3%	38.9%	4.6	4 478 847	5.6	613.4 (Above EU average)
Nordjylland (DK05)	110% (More developed region)	105% (More developed region)	6.90%	5.0%	-1.9%	31.8%	40.3%	8.5	589 926	2.7	76.4 (Below EU average)
Prague (CZ01)	190% (More developed region)	203% (More developed region)	3.10%	2.3%	-0.8%	46.8%	64.7%	17.9	1 335 084	6.7	2 714.3 (Above EU average)
Estonia (EE00)	76% (Transition region)	86% (Transition region)	8.60%	6.2%	-2.4%	42.5%	43.1%	0.6	1 330 068	2.0	30.5 (Below EU average)
Pays de la Loire (FRG0)	97%	93%	8.80%	6.0%	-2.8%	43.5%	49.7%	6.2	3 818 421	4.1	118.3 (Above EU average)

[6] The EU average unemployment rate in 2013 was 10.6%

[7] The EU average unemployment rate in 2021 was 7.1%

[8] The EU average of tertiary education attainment in 2013 was 34.8%

[9] The EU average of tertiary education attainment in 2021 was 41.5%

[10] The EU average population density in 2021 was 109

	(More developed region)	(More developed region)									
Malta (MT00)	89% (Transition region)	102% (More developed region)	6.10%	3.4%	-2.7%	28.7%	43.7%	15.0	514 564	23.3	1 595.1 (Above EU average)
Lisbon (PT17)	106% (More developed region)	96% (More developed region)	18.50%	6.8%	-11.7%	35.7%	50%	14.3	2 863 272	2.0	1 015.9 (Above EU average)
Dolnoslaskie (PL51)	75% (Transition region)	86% (Transition region)	11.30%	4.0%	-7.3%	36.8%	55.3%	18.5	2 864 889	1.1	144.9 (Above EU average)
Közép-Dunántúl (HU21)	61% (Less developed region)	70% (Less developed region)	8.70%	2.1%	-6.6%	27.3%	54.5%	2.4	1 060 755	2.5	99.1 (Below EU average)
Latvia (LV00)	63% (Less developed region)	72% (Less developed region)	11.90%	7.6%	-4.4%	40.7%	47.7%	7.0	1 907 675	-4.1	30.2 (Below EU average)

Pillars (2023), based on Eurostat data

2.2 Data collection and analysis of case studies

The collection and analysis of data for the case studies were guided by three research questions:

- **What policy approaches and instruments** of a region have successfully **stimulated creation of innovative and inclusive jobs**, powered by automation technologies, and **why**?
- What **policy approaches and instruments** of a region have successfully **prevented and mitigated job displacement**, following adoption of automation technologies, and **why**?
- What **policy approaches and instruments** of a region have successfully **supported employers and employees during job transformation**, following adoption of automation technologies, and **why**?

As mentioned earlier, the data collection for the case studies included three research methods: literature review (academic and grey), interviews, and validation of findings with the ESG members and workshop participants. Given a broad scope of the study and its exploratory nature, the project team faced **three major challenges**:

- **Identification of successful policy approaches and instruments**, given that each region has been applying various strategies and dozens of policy instruments/measures in different policy domains (innovation, entrepreneurship, education, employment, labour mobility etc) across years or even decades that, in combination, contributed to success;
- **Selection of key successful policy approaches and instruments that should be highlighted in case studies**, as each case study should be presented in a user-friendly and relatively concise format to ensure that it will be utilised by the policymakers and other stakeholders;
- **Determination of success factors of selected policy approaches and instruments**, especially those that are context-dependent, to analyse their relevance and transferability in other regions and to formulate generic lessons learned.

Above-listed challenges presented difficulties not only to the project team, but also to the identified experts, as they required substantial analysis and, to some degree, simplification/concentration of a narrative in case studies. Despite the ambition to present the most successful policy approaches and instruments in each region, the ultimate goal of the analysis is to draw generic lessons on how to stimulate job creation, address job displacement and support employers/employees during job transformation, following technological transformation. Above-listed challenges and limitations have been acknowledged, but not considered pivotal for the quality and usefulness of the analysis, as well as, for the illustration of good practices to the policymakers and stakeholders.

The process of data collection and analysis has followed these steps:

Step 1: Review of literature on labour market developments and technological transformation in a region to understand the general context and factors that may impact successfulness of policy approaches and instruments;

Step 2: Review of main policy approaches and instruments to address labour market developments by the project team, and pre-selection of most successful among them;

Step 3: Discussion of successful policy approaches and policy instruments, barriers and success factors with the interviewees, and verification of findings from Step 1 and 2;

Step 4: Triangulation and analysis of findings, and case study drafting.

The ultimate decision on what policy approaches and policy instruments should be highlighted in case studies has been made **in consultation with the interviewed experts**. The criteria for determining successfulness of policy approaches and policy instruments have been their **impact** on job creation, job displacement and job transformation. In many cases, evaluations and assessments of policy approaches and policy instruments have not been conducted in regions. For this reason, some interviewees suggested EU-funded policy instruments, as they are typically evaluated. To ensure diversity of policy instruments, the team relied on evaluated instruments, as well as, on suggestions from consulted experts and stakeholders. This implied that the team has not evaluated each individual instrument, but focused on the collection of **success factors** that, in view of consulted stakeholders or of previous evaluators, indicate that an instrument represents a good practice. In addition, preference has been given to **innovative** policy approaches and instruments, as they allow to gain insight into new possible solutions.

Given the significant role of interviewees for the study, the project team carefully selected them. Each case study involved **at least 3 interviewees** and at least 1 of them had to be a policymaker/public authority involved in the design, implementation, monitoring and/or evaluation of policies. Other interviewees could represent the industry, academic or civil society sectors. All interviewees had to had expertise in **at least one core domain** of the PILLARS project:

- Innovation, Industry and Entrepreneurship;
- Education and Training;
- Labour Market and Social Protection;
- Migration and Labour Mobility.

The literature review (Step 1 and 2) of the data collection and analysis process assisted the project team in the selection of suitable interviewees. In addition, the project team welcomed suggestions of already consulted stakeholders. Overall, interviewees have been very supportive of the project, as they shared relevant materials and indicated what other organisations should be interviewed for the purpose of the study. Prior to data collection, all interviewees have been informed about the ethics procedures of the PILLARS projects and signed participant consent forms.

All project team members followed a **uniform interview guide and a template for the case studies** to allow data analysis across the case studies. The template included **6 chapters**:

1. Introduction (geographic, demographic, economic, and if relevant political, context of a region);
2. Overview of the labour market in a region (labour market trends and skills in demand, major job sectors/industries, key challenges on the labour market and vulnerable groups);
3. Technological transformation and policies/instruments to stimulate innovative and inclusive job creation;
4. Policies/instruments to prevent and mitigate job displacement;
5. Policies/instruments to support employers and employees during job transformation;
6. Lessons learned (summary of key lessons learned across three labour market effects).

The case studies included data on selected labour, demographic and economic indicators from Eurostat and presented them in **tables**. The good policy instruments that have been identified across the case studies were **placed in boxes**.