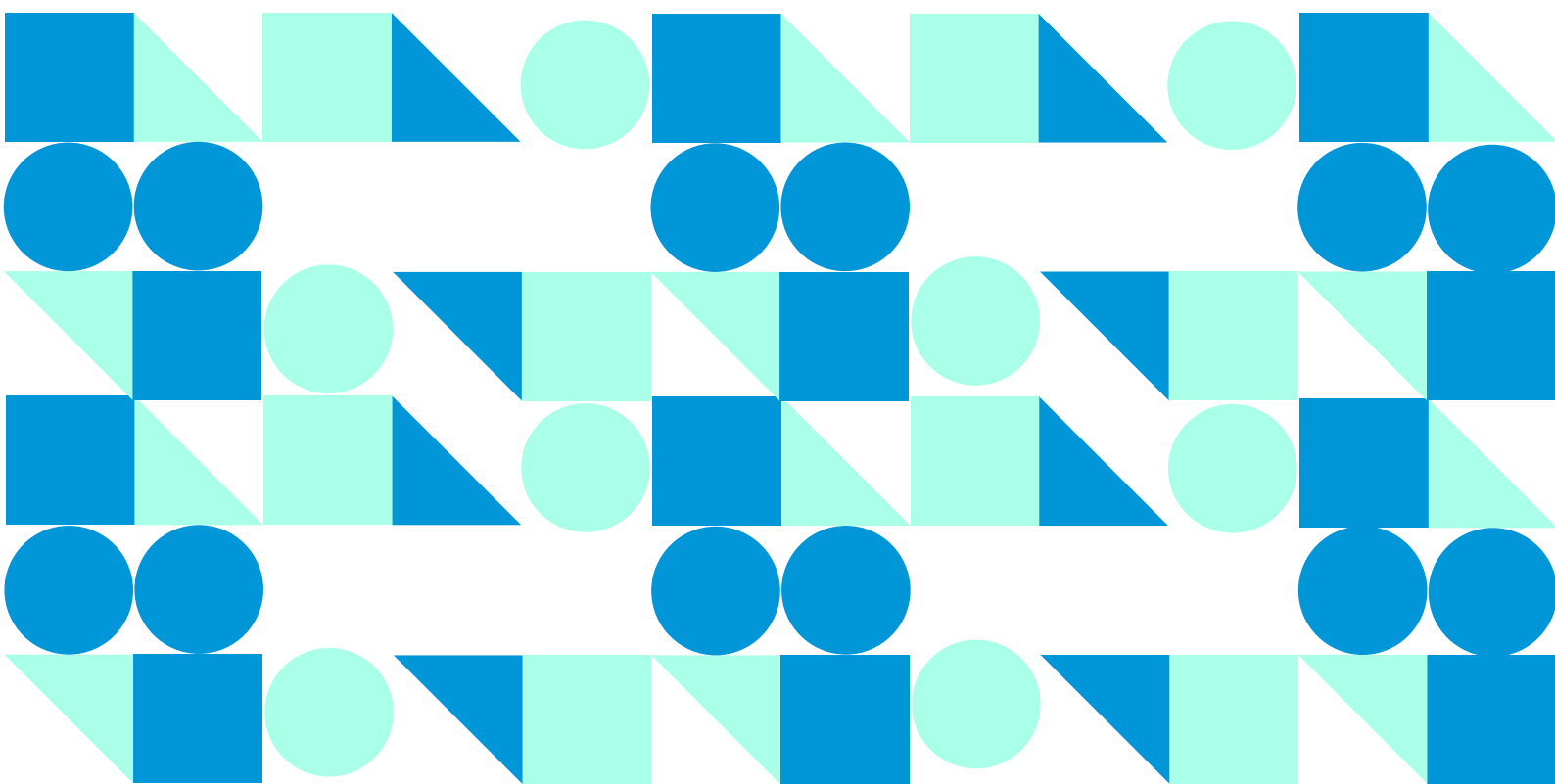




Research paper

Regional Skills Ecosystems index (RESET)

Leveraging Europe's competitiveness with
cutting-edge regional skills intelligence





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Leveraging Europe's competitiveness with cutting-edge
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Foreword

Skills are at the heart of Europe's capacity to be competitive, to manage the green and digital transitions and to ensure that economic growth translates into opportunity for all. Yet skills do not develop in a vacuum. They are shaped by regional labour markets, education and training systems, and skills environments, forming what can be understood as regional skills ecosystems. Despite growing recognition that these ecosystems vary enormously across Europe, so far no European Union (EU) tool has been available that assesses and compares them systematically at the regional level.

The Regional Skills Ecosystems index (RESET) fills this gap. It brings together 37 indicators across four skills pillars for 244 NUTS 2 (nomenclature of territorial units for statistics, level 2) regions across all EU Member States. RESET offers for the first time a structured, comparable and evidence-based assessment of how regions develop, deploy and match skills. RESET includes indicators specific to individuals in vocational education and training (VET) alongside indicators for the broader population. The set-up is aligned with EU policy, which places VET at the centre of the European skills agenda.

This research paper documents how the index was built. It provides an overview of the literature, conceptual framework and indicator selection, and outlines technical details such as data treatment, normalisation, weighting, aggregation, statistical coherence and robustness checks.

RESET arrives at a time when the policy demand for regional skills intelligence has never been greater. The Council recommendation on human capital in the EU calls on Member States to integrate skills intelligence into regional and local strategies. It also acknowledges the important territorial dimension of employment and skills challenges across Europe. This dimension has also been emphasised by the European Skills High Level Board, advocating for the creation of high impact regional and sectoral skills ecosystems. RESET responds to these growing policy needs and complements Cedefop's skills intelligence work by adding regional granularity.

RESET is still at an early stage and will continue to grow. As new data become available, and as feedback from regions and policymakers shapes its further development, it has the potential to become a reference tool for evidence-based regional skills policy across Europe. We hope that this research paper will serve as a methodological reference and as an invitation to policymakers and practitioners working on skills and VET to engage with the index, to use it to

validate and enrich labour market expertise, and to help us refine it so that it becomes the tool that Europe's regions need.

Jürgen Siebel
Cedefop Executive Director

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Executive summary

The Regional Skills Ecosystems (RESET) index is a significant step forward in the development of intelligence for regional skills ecosystems in the European Union (EU). Developed as a regional-level composite index, RESET is designed to complement existing EU regional statistics and indices and national-level skills intelligence tools and frameworks.

RESET introduces a much-needed regional lens to skills and to vocational education and training (VET), highlighting their pivotal role in fostering inclusive and sustainable growth and in addressing the twin challenges of the green and digital transitions. Unlike existing national skills anticipation and intelligence tools, RESET delves into the complexities of regional VET and skills ecosystems. Regional intelligence about skills supply, demand, development, use and matching offers policymakers a unique opportunity to design more effective skills strategies.

RESET builds on and complements Cedefop's national-level tools, such as the European skills index (Cedefop, 2026a) and the key indicators on VET (Cedefop, 2026b). RESET is the first comprehensive regional index focusing on VET and skills in the EU. It provides data for 244 NUTS 2 (nomenclature of territorial units for statistics, level 2) regions for the reference year 2024. The added value of this innovative index arises not only from the application of a composite indicator approach at the regional level but also from the creation of new regional indicators.

Skills are the bedrock of productivity, innovation and economic growth. The Draghi report on the future of European competitiveness (European Commission, 2024), the European Commission initiative on the Union of Skills (European Commission, 2025a) and the Council recommendation on human capital in the EU (Council of the European Union, 2026) place skills at the heart of Europe's policy debate. RESET fully incorporates the notion that skills development, use and matching takes place within complex ecosystems comprising education and training providers, businesses, workers and learners. Thanks to adopting an ecosystem approach, RESET helps identify the conditions that make skills ecosystems thrive.

RESET comes at a time where there is broad consensus about the importance of equipping Europe's workforce to navigate the green and digital transitions. Ongoing shifts and skills upgrading transform labour markets and sectors and demand advanced technical competences and sustainability-oriented skills. VET is responsive to emerging skills needs by design, and it plays a key role in mitigating skills mismatches. Thanks to these features, VET is a cornerstone of

regional skills ecosystems and a source of empowerment for people who need to remain competitive in a rapidly changing economic landscape. RESET underscores the critical role of VET not only in promoting efficient education-to-work transitions but also in sustaining employability and advancing lifelong learning.

This research paper outlines RESET's development process. It presents a literature review, describes the methodological framework of RESET and provides details on data collection, imputation, outlier treatment, normalisation and aggregation. These steps ensure the index's reliability and robustness, and correlation analysis, sensitivity, uncertainty and principal component analyses validate its methodology. The research paper demonstrates that RESET is grounded in a robust methodological framework, both conceptually and statistically. Correlation analysis points to a strong degree of internal consistency, while the uncertainty analysis shows that most regional rankings remain stable within acceptable margins. Advanced sensitivity decomposition indicates that the aggregation method is the main driver of ranking variation, whereas normalisation and weighting make more limited contributions and imputation has only a negligible effect.

Principal component analysis results are consistent with these findings: where indicators within each component are highly coherent and make broadly similar contributions to the underlying dimension, changes in weights are expected to have only a limited influence on the results, as confirmed by the sensitivity analysis. Taken together, these findings show that RESET offers a reliable and robust basis for comparing skills ecosystem performance across regions and captures real differences in skills ecosystems.

RESET is publicly available via Cedefop's web portal. Cedefop would like it to become a trusted and vital resource for policymakers, researchers and other stakeholders. The comparative analysis of regional skills ecosystems that RESET offers facilitates targeted interventions, strengthens regional economies, and supports European ambitions for inclusive and sustainable growth in a globally competitive landscape.

Chapter 1.

Introduction

‘The foundation of Europe’s competitiveness is its people’
‘A Competitiveness Compass for the EU’ (European Commission, 2025b, p. 22)

The **REgional Skills EcosysTems** index (RESET) represents a significant advancement in understanding and evaluating regional skills ecosystems in the European Union (EU). Developed as a composite index at the NUTS 2 (nomenclature of territorial units for statistics, level 2) ⁽¹⁾ regional level, RESET fills a vital knowledge gap in the EU by focusing on skills ecosystems – an area increasingly recognised as a key driver of economic growth and competitiveness.

RESET introduces a regional lens to skills and vocational education and training (VET), which are pivotal for achieving sustainable growth and meeting the challenges of the green and digital transitions. While Cedefop has developed influential national-level tools such as the European skills index (Cedefop, 2026a) and the key indicators on VET (Cedefop, 2026b), there has not yet been a comprehensive regional index focusing on VET and skills for all European regions. RESET addresses this gap by offering a tool that provides a nuanced perspective and captures regional disparities, strengths and weaknesses in skills ecosystems (see Box 1).

Box 1. **RESET**

RESET is now available on Cedefop’s website, making it widely accessible to stakeholders across Europe. Thus, [RESET](#) serves as a key resource, empowering policymakers to design better skills policies and fostering collaboration towards a skilled and resilient European workforce.

Source: Cedefop.

Skills are the foundation of individual employability, and they are enablers of broader economic and societal objectives, including productivity, innovation and social cohesion. The Draghi report on the future of European competitiveness (European Commission, 2024) highlights the essential role of skills in fostering economic growth and maintaining Europe’s global competitiveness. In March

⁽¹⁾ NUTS is the official classification of regions in the EU.

2025, the Commission adopted a communication on the Union of Skills (European Commission, 2025a), which positions human capital and future-oriented skills as central to strengthening competitiveness. The communication proposes a new approach that brings together education, training, and employment policies around a common vision, supported by enhanced skills intelligence and stronger governance (European Commission, 2025a). The Competitiveness Compass, adopted in January 2025 (European Commission, 2025b), complements the Union of Skills. The compass identifies skills as one of the critical enablers of economic dynamism, and recognises the central role of a skilled workforce in driving productivity, innovation and the green and digital transitions.

The Council recommendation on human capital in the EU (Council of the European Union, 2026) signals the strong policy relevance of RESET. This landmark instrument, aimed at overcoming skills shortages in strategic sectors, calls on EU Member States to ‘strengthen fast-track as well as longer-term delivery of future-proof and labour market-relevant skills in areas of strategic importance, by fostering partnerships between education and training providers, public employment services, social partners and individual businesses as well as public bodies, including at regional and local levels’ (Council of the European Union, 2026, recommendation 1). RESET’s regional perspective directly addresses this recommendation by providing the granular, sub-national evidence needed to identify where stronger partnerships are most needed and where skills ecosystems are functioning effectively.

The Council recommendation also emphasises the importance of skills intelligence for mastering labour market transitions. It recommends that Member States ‘Further integrate and increase the regular use of skills intelligence in the (re-)design of national, regional and local skills and economic development strategies’ (Council of the European Union, 2026, recommendation 6). RESET responds to this call by providing a structured, composite measure of regional skills ecosystem performance that can inform the design and implementation of such strategies. The recommendation acknowledges that employment policies have ‘an important territorial dimension, with significant territorial differences across Europe in skills and human capital endowment’ (Council of the European Union, 2026, recital 6). RESET’s ecosystem approach to understanding human capital provides a holistic framework for understanding how regions can develop the workforce capacity needed to address the economic and social challenges they face.

RESET can inform policy development and implementation at a time when skills are central to Europe’s twin transitions. The digital transition demands advanced technical and digital competences, and the green transition requires new skills and mindsets to support sustainable industries and practices. These

transitions necessitate upskilling and reskilling of the workforce and a coherent skills policy and support framework that ensures these skills are properly communicated to learners and workers, and skills are accessible, relevant and effectively utilised.

VET plays a pivotal role in regional skills ecosystems because it effectively bridges education and employment. It equips individuals with the practical, technical and often industry-specific skills required in modern economies, enabling them to transition seamlessly into the workforce. As technological advancements and the twin digital and green transitions reshape labour markets (Fouquet and Hippe, 2022), VET has become an indispensable component of workforce development and adaptation strategies.

VET's core strengths are its close alignment with industry needs (Cedefop, 2025a) and its contribution to upskilling and reskilling efforts. As sectors undergo digital transformation and adapt to become more sustainable, many workers need to acquire new competences or update their existing skill sets, such as artificial intelligence skills for the workplace (Cedefop, 2025b). VET programmes, and the work-based learning opportunities they provide, create accessible and targeted training opportunities that empower individuals to remain employable and productive.

RESET acknowledges the strategic importance of VET in fostering resilient and innovative regional economies. By incorporating indicators related to VET and skills, RESET highlights the contribution of human capital investment, matching and use to addressing regional disparities in skills development. The insights RESET provides support policymakers in designing targeted interventions to enhance and upscale VET provision, to increase accessibility and to ensure alignment with economic priorities and competitiveness ambitions.

In the context of Europe's broader ambitions, VET is central to achieving the goals of the [European Green Deal](#), the [Clean Industrial Deal](#), the [Digital Compass 2030](#) and the Digital Decade policy programme. These policy initiatives emphasise why the twin transitions crucially rely on a skilled workforce that can drive change. VET not only prepares young people for labour market entry but also supports people already in the labour market in adapting to new roles and moving to new jobs, ensuring that no one is left behind in the transformation.

RESET responds to a growing need for a dedicated tool to systematically assess regional skills ecosystems. It complements thematic indicator frameworks that include skills as only one element among many, such as the European Commission's Regional Innovation Scoreboard (European Commission, 2026b) and EU Regional Competitiveness Index (European Commission, 2022). By focusing on the dynamics of regional skills supply, demand, environment and

matching, RESET reflects the growing recognition that effective skills policy requires strong regional intelligence to capture regional economic structures, labour market conditions and institutional capacities. RESET gives policymakers a robust analytical tool to identify strengths and weaknesses in regional skills ecosystems. It supports evidence-based and proactive decision-making and helps prioritise interventions and target resources more effectively. Lagging regions can use RESET to benchmark their performance and draw lessons from their peers.

This research paper outlines the development and construction of RESET. It provides a comprehensive account of the methodological framework and technical details underpinning the index. The paper shows that leveraging advanced statistical techniques and integrating a broad range of indicators delivers a robust, insightful and policy-relevant tool.

The research paper includes a literature review on skills ecosystems. It delves into how these ecosystems have been conceptualised across various academic disciplines. The review highlights key articles, methodologies and thematic areas, ranging from the interplay of education policy and industry demands to the role of technological innovation in shaping new skills requirements. This helps set a foundation for understanding how to foster more resilient and dynamic skills ecosystems and how to reflect it in the set-up of RESET.

The core of this research paper explains the methodological approach Cedefop has taken to constructing RESET, ensuring reliability and comparability. This includes data selection, imputation techniques, outlier treatment and normalisation approaches. The research paper also elaborates on the aggregation methodologies employed, and reports on the sensitivity, uncertainty and principal component analyses conducted to validate the robustness of the index. These are critical in guaranteeing that RESET provides an accurate and meaningful representation of regional skills ecosystems. The paper concludes by reflecting on potential future developments of the index and accompanying projects.

Chapter 2.

Literature review

2.1. Definitions

While skills are key to innovation and economic development (Mankiw et al., 1992; Glaeser et al., 2004; Acemoglu and Autor, 2012; Hanushek & Woessmann, 2016; Diebolt & Hippe, 2019), there have been major differences in their regional distribution in Europe both today and over the last 200 years (Rodríguez-Pose & Crescenzi, 2008; Gennaioli et al., 2013; Baten & Hippe, 2018; Diebolt & Hippe, 2018; Hippe & Fouquet, 2019). These regional inequalities are an outcome of unique features of regions and differences in underlying skills ecosystems.

The variety of definitions of the concept of skills ecosystems in the academic literature reflects its multifaceted nature. For example, Buchanan et al. define skills ecosystems as ‘clusters of high, intermediate, or low-level competencies in a particular region or industry shaped by interlocking networks of firms, markets, or institutions’ (Buchanan et al., 2001, p. 21). This definition emphasises the geographical and sectoral clustering of skills and the interconnectedness of various actors. Windsor and Alcorso describe a skills ecosystem as ‘a self-sustaining network of workforce skills and knowledge in an industry or region’ (Windsor & Alcorso, 2008, p. 5), a definition that highlights the continuous, cyclical nature of skills development and utilisation. The Organisation for Economic Co-operation and Development (OECD) expands the scope by defining local skills ecosystems as ‘a cluster of firms working horizontally across a value chain with the education and training system to foster knowledge exchange and coordination’ (OECD, 2018, p. 57). Edwards et al. emphasise the role of relationships and interactions by describing skills ecosystems as encompassing ‘the capabilities, relationships, and interactions between individuals and institutions’ (Edwards et al., 2021, p. 5).

Cedefop defines skills ecosystems as a ‘[c]ommunity (businesses, industry/sector, education and training providers, [non-governmental organisations], local or regional stakeholders, etc.) in which individuals and organisations connect and interact to address skills needs and develop, use and transmit, in an autonomous way, knowledge, abilities and competences’ (Cedefop, 2026c).

In the context of RESET, we can thus consider skills ecosystems the interactions among education and training providers, employers and the respective skills environments that generate positive outcomes for skills supply, demand and matching. This captures the dynamic interplay of actors and the systemic

outcomes essential for fostering resilient regional skills ecosystems (see also Cedefop, 2012).

2.2. Origins of the skills ecosystem concept

The notion of the skills ecosystems is rooted in ecological concepts from the biological sciences, adapted to address challenges in business, economics and policy (Windsor & Alcorso, 2008). The idea emerged as a reaction to persistent problems such as skills shortages, underutilisation of available skills, a rise in low-skill work, job polarisation and the externalisation of upskilling costs to individuals and the state (Payne, 2007, 2008; Shapiro, 2011). Skills ecosystems propose an alternative to ‘one-size-fits-all’ workforce upskilling policies by tailoring strategies to the specific needs and interdependencies of actors within a given region or sector (Payne, 2008).

According to Buchanan et al. (2017), the concept of skills ecosystems also challenges traditional supply-side approaches to skills policy, which often assumed that increasing education levels would suffice for international competitiveness. Instead, the ecosystem perspective argues that the context in which skills are developed and deployed is critical. Skills only yield value if they are productively used. While this complexity makes skills ecosystems challenging to understand, design and implement, it also offers a more nuanced framework for addressing the multifaceted relationship between skills and economic growth (Payne, 2008).

The intellectual foundations of the skills ecosystem concept go back to Adam Smith’s exploration of the interplay between skills and economic growth. The more immediate predecessors of this concept can be traced to mid-20th-century studies of national skill equilibria, which linked skills and economic performance to human capital policy frameworks and institutional practices. In these studies, countries with ‘high-skill equilibria’ were shown to perform better economically, but achieving such equilibria required a comprehensive mix of policy initiatives and reforms. While they provided new insight, these national-level approaches were not able to shed a light on intra-national variations in skills and performance (Buchanan et al., 2017).

2.3. Ecosystem levels and contextual factors

Finegold (1999) expanded the scope of skills-related research by introducing a geographical lens to skills development and coining the term ‘skills ecosystem’. His work highlighted the existence of skill clusters within countries or across borders,

arguing that geographical proximity offers advantages for clustering activities and resource exchange. Finegold defined a high-skill ecosystem as ‘a geographic cluster of organisations (both firms and research institutions) employing manpower with advanced, specialised skills in a particular industry and/or technology’ (Finegold, 1999, p. 61). Drawing inspiration from Porter’s ‘diamond model’ (Porter, 1990), Finegold identified four key drivers of self-sustaining skills ecosystems: a catalyst (e.g. funding), a supportive environment (e.g. infrastructure, regulation), sources of nourishment (e.g. VET institutions, universities) and strong interdependence among actors.

Finegold’s framework focused on high-skill, hi-tech ecosystems, exemplified by Silicon Valley. Here, government funding acted as a catalyst, while universities provided a continuous stream of highly skilled workers. Complementary local factors, such as robust infrastructure and a business-friendly regulatory environment, supported the ecosystem’s growth. The interconnectedness of local actors (e.g. firms with complementary expertise) enabled informal knowledge sharing, driving innovation and fostering workforce development. While some ecosystems, like Silicon Valley, emerge organically, others require deliberate policy interventions to catalyse growth. Institutions like universities or VET centres often serve as anchors for such systems (Cedefop, 2012; OECD, 2018).

Windsor and Alcorso (2008) differentiated between high-skill ecosystems and low-skill ecosystems. High-skill ecosystems are characterised by competitive advantages, innovation and high wages, while low-skill ecosystems are defined by low productivity, low wages and low value-added outputs. These mutually reinforcing dynamics underscore the importance of understanding why certain regions or sectors pursue high-skill strategies while others remain in low-skill cycles.

2.4. Matching skills supply and demand

Central to the skills ecosystems approach is balancing the supply and demand sides of skills development. Education and training systems, particularly VET, must adapt to dynamically evolving labour market needs while also maintaining a long-term strategic perspective. On the supply side, education or training programmes, skill profiles, school-to-work transitions and guidance can be revised to better align with industry needs. On the demand side, optimising skills use involves adapting work and workplace processes, adapting talent management, leveraging technology and developing competitive business strategies (Shapiro, 2011). Effective ecosystems strengthen skills demand and supply and their prospects of being well matched, simultaneously improving business performance and

generating positive outcomes for workers (Windsor & Alcorso, 2008; Cedefop, 2015, 2018; McGuinness et al., 2018).

Supply-side approaches often risk ‘producer capture’ wherein training programmes become misaligned with labour market demands, because the provider interest dominates, not the market, which results in inefficiencies (Buchanan et al., 2017). Conversely, demand-side strategies can lead to skills shortages and fragmentation, as firms focus on short-term needs without investing in training that serves long-term skills needs (Cedefop, 2015). A balanced ecosystem approach integrates these perspectives, fostering a synergistic relationship between skills provision and utilisation (Hall & Lansbury, 2006; Erickson et al., 2025).

2.5. Challenges and advantages of the ecosystem approach

While skills ecosystems present advantages, such as fostering collaboration and equitable distribution of training costs, they are also complex to sustain. Establishing trust and consensus among stakeholders and coordinating efforts require substantial time and resources. Engaging companies, particularly those resistant to change, is a challenge. Moreover, effective ecosystems rely on knowledgeable intermediaries who can facilitate dialogue and maintain relationships (Evesson & Oxenbridge, 2013; Buchanan et al., 2017). Despite these challenges, the ecosystem approach offers unique benefits. It encourages employers to take ownership of their skills needs, reduces free-riding behaviours, and improves the matching between skills provision and labour market needs.

2.6. Implications for the development of RESET

Cedefop used insights from the literature on skills ecosystems to develop RESET. First, RESET captures the multidimensional nature of skills ecosystems, reflecting their inherent complexity. This involves considering the supply of skills, provided by VET institutions and other educational system actors, the demand for skills from employers and contextual factors that enable or constrain the systems.

The ecosystem literature also highlights the importance of considering regional variation, an insight that aligns well with RESET’s focus on NUTS 2 regions. Buchanan et al. (2001, 2017) show that skill levels and their associated ecosystems vary widely, even within national boundaries. This calls for an index that is sensitive to regional specificities. Incorporating these features will help

ensure that RESET provides a nuanced view of regional skills ecosystems and offers actionable and policy-relevant insights.

Another critical challenge is balancing supply and demand factors in the RESET framework. The literature has uncovered the risks of focusing exclusively on either side, such as the inefficiencies of supply-driven approaches and the fragmentation of demand-driven strategies. By integrating metrics that capture skills development, matching, environment and use, RESET strikes a balance between skills demand and supply.

In conclusion, the literature provides robust conceptual foundations for RESET, offering guidance on what aspects to include and measure and why. By integrating these insights, RESET can become a comprehensive tool for evaluating and improving regional skills ecosystems, ultimately supporting more effective and equitable VET and skills policies across the EU.

Chapter 3.

Composite indicator construction

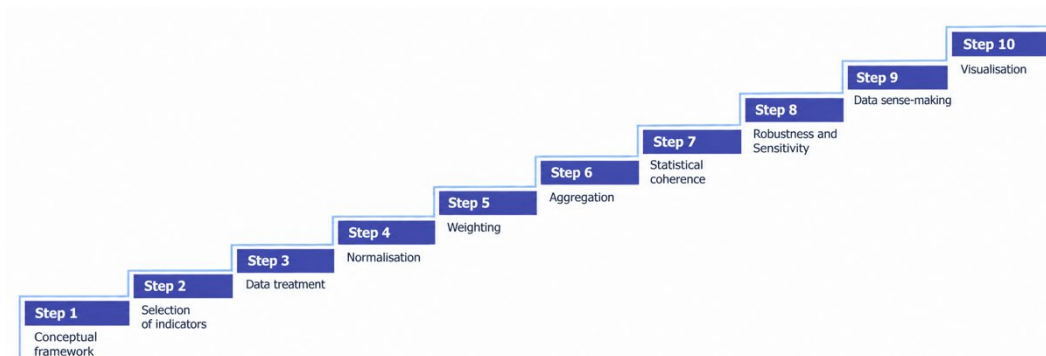
Composite indicators are invaluable tools for summarising complex, multidimensional phenomena into a single metric, making them highly effective for policy analysis, benchmarking and public communication. The possibilities they offer to condense large volumes of information into an easily accessible and interpretable format enables policymakers and stakeholders to identify trends, assess performance and make informed decisions.

Constructing a reliable and meaningful composite indicator is a complex process that requires a systematic and rigorous approach to ensure both scientific soundness and practical relevance. The influential *Handbook on Constructing Composite Indicators* by the European Commission's Joint Research Centre (JRC) and the OECD (Nardo et al., 2008) outlines a 10-step framework for building robust composite measures. This framework has been further refined and updated, as reported in the European Commission's materials for the JRC Week on Composite Indicators and Scoreboards (European Commission, 2023a). As they are more up to date, we used the most recent framework to guide the construction of RESET (Figure 1) ⁽²⁾.

All steps for developing a composite indicator require meticulous attention. The stages include defining the conceptual framework, selecting appropriate indicators, handling missing data, addressing outliers and applying suitable normalisation, weighting and aggregation techniques. The approach also attaches importance to coherence, sensitivity and uncertainty analyses to validate the robustness of the index.

⁽²⁾ In this chapter, we follow the respective methodologies of the JRC and OECD (Nardo et al., 2008) and the European Commission (2023a), which are implemented and further described in practical terms by the R package COINr and its documentation (Becker et al., 2022). They are the main references on which the text describing the specific details of the methods is based. We thus do not reference them in each section.

Figure 1. 10-step approach used to construct RESET



Source: European Commission, 2023a (edited).

The development of RESET closely follows the structured JRC and OECD methodology to ensure that the resulting composite indicator is statistically robust and meaningful for regional comparisons. RESET integrates each of these steps to address the unique challenges posed by multidimensional data. For instance, it employs robust outlier detection and treatment, followed by min–max normalisation to align all indicators on a scale of 1 to 100 to ensure comparability. Indicators are then aggregated using a simple weighting scheme, reflecting their relative importance to the overall index. These methodological choices are guided by the principles outlined in the JRC and OECD handbook and were fine-tuned through discussions with colleagues at Cedefop and the JRC Competence Centre on Composite Indicators and Scoreboards (COIN) team members during the COIN open day in October 2025 (European Commission, 2026a).

3.1. Conceptual framework

Establishing a robust theoretical framework is the foundation for constructing a composite indicator. This step involves defining the phenomenon to be measured and breaking it down into components. The process of selecting indicators that best represent the various aspects of the phenomenon and determining the weights for these indicators based on their relative importance within the composite measure should be guided by a well-defined conceptual model that outlines the relationships among the components and their contribution to the phenomenon. The theoretical framework ensures that the composite indicator is coherent and scientifically validated, and it provides clarity and direction throughout the subsequent development steps.

RESET is grounded in a robust conceptual framework capturing the complexity of skills creation, skills matching and utilisation, and contextual

influences, as pointed out in Chapter 2. This framework has four pillars: skills supply, skills demand, skills environment and skills match (Figure 2). Each pillar represents a key dimension of the skills ecosystem. The RESET pillars and the index they feed into provide policymakers with insights to address skills-related challenges and to strengthen regional competitiveness. The development of RESET builds on existing knowledge, incorporating theoretical foundations, empirical evidence and insights from Cedefop's extensive research into skills and labour market dynamics.

Figure 2. **Index structure**



Source: Cedefop.

The skills supply pillar examines how skills are developed within a region. This dimension is informed by Becker's (1964) human capital theory, which highlights the role of education and training in enhancing productivity and economic growth. RESET emphasises the importance of aligning education and training systems with regional needs. Lifelong learning, an essential element of skills supply, is critical for equipping individuals with the capabilities needed to navigate rapidly changing labour markets. Cedefop's (2020) work on upskilling and reskilling underscores the importance of continuous education in enabling workers to meet evolving demands, particularly in the context of the digital and green transitions.

The skills demand pillar focuses on the use of available skills. Among others, it is related to the task-based approach, which offers a granular perspective on how

tasks performed in jobs drive the demand for specific skills (Autor et al., 2003; Autor & Handel, 2013; Handel, 2016; Cedefop, 2024a, 2024b). This theory categorises tasks as routine or non-routine and cognitive or manual (Fernández-Macías & Bisello, 2022), explaining how technological change or outsourcing or, in the context of the Coronavirus disease 2019 (COVID-19) pandemic, the potential to telework may be dictated by task allocation across occupations and affect labour market outcomes accordingly. For example, non-routine cognitive tasks, such as problem-solving and creative thinking, have been increasingly in demand due to their complementarity with digital tools, while occupations reliant on routine, non-cognitive tasks have faced a greater risk of machine replacement. RESET uses this approach to assess occupational skills requirements at the regional level, linking the prevalence of tasks to the skills needed in those regions. This helps identify gaps in task-specific skills and provides actionable insights for upskilling and reskilling policies and actions.

The skills environment pillar evaluates the broader context in which skills ecosystems operate, including institutional quality and cooperation. Drawing on North's (1990) theories of institutional development, this dimension considers how governance and business climate shape regional capacities for skills development and use. By integrating these contextual factors, RESET ensures a comprehensive understanding of how external influences shape regional skills ecosystems. This dimension is particularly relevant in the context of Europe's twin transitions, where supportive environments are essential for fostering innovation and addressing workforce shortages and skills gaps.

The skills match pillar addresses barriers to effective skills development and utilisation, such as mismatches between workforce capabilities and labour market needs. Mismatches, a significant focus of Cedefop's European skills and jobs surveys (2018, 2024a), signal inefficiencies that can foster underemployment, lead to poor job equilibria and impede economic growth and social cohesion. RESET examines structural and systemic matching challenges, including the transitions from education to employment, which are critical for integrating young people into the workforce. These challenges reflect broader societal issues, such as youth unemployment and regional disparities, which RESET aims to place in the spotlight. By identifying areas where regional systems fall short, the RESET skills match pillar provides evidence for targeted interventions that enhance labour market inclusivity and efficiency.

RESET's conceptual framework reflects a holistic approach to understanding regional skills ecosystems. The four pillars jointly facilitate a nuanced analysis of how skills are created, used and influenced by broader systemic skills ecosystem features. This multidimensional perspective is critical for addressing Europe's

complex skills challenges and supporting the policy objectives outlined in the Union of Skills and other EU skills policy initiatives.

3.2. Data selection

Data selection is a critical step in the construction of a composite indicator, as the quality and relevance of the data directly impact the robustness of the final measure. The data selection process involves choosing indicators based on criteria such as relevance to the phenomenon being measured, analytical soundness, measurability, geographical and temporal coverage, and their interrelationships. In cases where direct data are not available, proxy measures may be used. Ensuring data quality involves verifying the integrity, accuracy and consistency of the selected data sources. Data selection should also consider the availability of historical data to enable trend analysis, and the likely regularity of future updates. The selected data must be capable of providing a comprehensive and accurate representation of the different dimensions of the phenomenon, forming a reliable foundation for constructing the composite indicator.

3.2.1. Exploration of data and information sources

Figure 3 shows the diverse and extensive range of potential data sources that has been explored for inclusion in RESET. These sources bring together a variety of sectors and themes, ensuring a comprehensive and multidimensional approach to capturing relevant data. The wide scope of these sources facilitated the efforts to create high-quality, reliable and internationally recognised indicators that address the core dimensions of skills supply, demand, environment and matching.

Figure 3. Examples of consulted sources

- Cedefop – European Centre for the Development of Vocational Training - Clarivate InCites - CORDIS - CWTS – Leiden Ranking - Digital Innovation Hubs - EQAR – European Quality Assurance Register for Higher Education - Erasmus+ - ESPON - ETER – European Tertiary Education Register - EU Code Week - EU Media Monitor - Eurobarometer - European Cluster Collaboration Platform - European Commission - European Committee of the Regions - European Environment Agency	- European Investment Bank - European Patent Office - European School Education Platform - European Social Survey - European Statistical System - European Vocational Skills Week 2023 - Eurofound - Eurostat - eTwinning - Joint Research Centre (JRC) - KNOWMAK – Knowledge in the Making in the European Society - Microsoft - Numbeo - OECD - Orbis - PISA	- QoG – The Quality of Government Institute - QS World University Rankings - RISIS – Research Infrastructure for Science and Innovation Policy Studies - ROR – Research Organization Registry - SCImago Institutions Rankings - Smart Specialisation Platform - The Cultural and Creative Cities Monitor - Times Higher Education World University Rankings - U-Multirank - UNDP – United Nations Development Programme - United Nations - Web of Science - Webometrics – Ranking Web of Universities - WHED – World Higher Education Database
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Source: Cedefop.

The sources consulted span across statistical agencies, research institutions, international organisations and rankings platforms, and each contributes unique insights. For example, official data providers such as [Eurostat](#), the [European Statistical System](#) and the [OECD](#) deliver standardised and internationally comparable statistics and indicators on education, labour markets, productivity and related concepts. The methodological rigour and data reliability that these organisations provide are foundational for the index. Additional institutional sources such as the [European Commission's JRC](#), [Cedefop](#) and [Eurofound](#) bring data and indicators on employment, social issues and skills mismatches.

Surveys such as the [European Social Survey](#) provide valuable indicators on education quality and societal factors influencing skills ecosystems.

Research and innovation-focused infrastructure and projects such as the [Research Infrastructure for Science and Innovation Policy Studies](#) generate valuable data on innovation, research outputs and skills development in knowledge-intensive sectors.

Similarly, ranking platforms such as the [Times Higher Education world university rankings](#), [QS world university rankings](#) and the [Leiden ranking](#) offer insights into higher education quality, research output and international collaboration, and shed light on the performance and competitiveness of education systems.

Platforms like [Erasmus+](#) and [eTwinning](#) emphasise digital education, research, innovation and cross-border learning initiatives, and they deliver information and data relevant to (lifelong) learning and digital transformation.

Niche sources and tools such as [Numbeo](#) can capture the contextual and quality-of-life factors influencing regional skills ecosystems. The [European Cluster Collaboration Platform](#) and other business-oriented platforms focus on mapping skills demand, productivity and industry innovation.

3.2.2. Criteria for data selection

While the diversity of explored data sources to be potentially included in RESET is impressive, not all sources meet the inclusion criteria. According to JRC and OECD (Nardo et al., 2008), the evaluation of data sources must adhere to specific quality standards to ensure the validity, reliability and usability of the final index. Therefore, the following criteria have been applied.

- (a) **Relevance.** This refers to the degree to which the data address current and potential needs of users. For the index, data must provide meaningful insights into skills supply, demand, environment and matching. If an indicator does not align directly with these dimensions or does not contribute to addressing policy-relevant questions, it cannot be included.
- (b) **Accuracy.** This measures how close estimates or computations are to the true values. Data sources must provide reliable, well-documented methods of data collection and calculation. For example, administrative data or survey results from reputable institutions like Eurostat, the OECD or the United Nations Educational, Scientific and Cultural Organization are typically prioritised because they meet rigorous quality standards.
- (c) **Timeliness.** This is critical for ensuring that the index reflects the most current realities of regional skills ecosystems. If there is a significant lag in data availability, data may no longer be relevant. For this reason, sources with outdated data or long production cycles are often excluded.
- (d) **Accessibility.** This relates to how readily the data can be obtained from its original source. Data from open-access platforms, such as Eurostat or the OECD, are preferred because they can be easily located, downloaded and integrated into analysis. In contrast, data that require costly licences or complex procedures to access tend to be impractical.
- (e) **Interpretability.** This ensures that users can easily understand and properly use the data. Indicators must be presented in a clear format with well-documented metadata, including definitions, methods and limitations. Overly complex or ambiguous data can undermine the transparency and usability of the index.

- (f) **Coherence.** This assesses the degree to which data are logically connected and mutually consistent. For example, data must align across time, regions and concepts. Disparate or incompatible datasets, even if they are valid in their own right, cannot contribute to a composite index without risking logical inconsistencies.

3.2.3. Definition of regions

A specific RESET feature is the requirement for regional-level data with comprehensive coverage across all EU Member States. This requirement significantly reduces the pool of eligible data sources, as many thematically relevant sources lack geographical or regional granularity.

NUTS 2 regions (see Box 2) are often considered a suitable level for constructing regional indices thanks to the balance between granularity and manageability. These regions provide sufficient opportunities to capture regional variations while remaining broad enough to align with administrative data availability and policy implementation. Other indices such as the [Regional Innovation Scoreboard](#) also use the NUTS 2 level, making it a de facto standardised approach in European statistical regional analyses ⁽³⁾.

Using NUTS has advantages and disadvantages. On the positive side, the widespread application of NUTS 2 regions in European statistical databases ensures that a wide array of relevant and high-quality data are readily accessible. This availability supports various regional indices, underscoring the utility and reliability of using NUTS 2 regions. On the downside, aggregating data at the relatively high NUTS 2 level might mask significant intra-regional variations, and contribute to a partial, distorted or oversimplified view of regional skills ecosystems.

The policy relevance of the NUTS 2 regional level is significant, as many EU policies and funding mechanisms are designed around them. This makes indices based on the NUTS 2 level directly relevant to policy analysis and decision-making. Nevertheless, as administrative boundaries of NUTS 2 regions might in practice not always be fully aligned with the natural or economic boundaries relevant to

⁽³⁾ It should be noted that the NUTS classification is periodically revised; the most recent versions relevant to RESET are NUTS 2021 and NUTS 2024. While RESET adopts the NUTS 2024 classification as its reference framework, several variables were only (partly) available under the earlier NUTS 2021 coding. A transformation of the regional classification from NUTS 2021 to NUTS 2024 was therefore carried out for these variables. The regions affected by this reclassification are in the Netherlands and Portugal.

skills ecosystems, they will not always produce completely accurate representations ⁽⁴⁾.

Comparability is another advantage; NUTS 2 regions provide a standardised framework facilitating comparisons across different regions within Europe. This helps with identifying best practices and performance benchmarking.

In conclusion, the NUTS 2 regional classification offers a feasible middle ground, as it provides sufficient granularity to capture regional differences without becoming too fragmented. This is a foundation for analysing regional strengths and weaknesses.

Box 2. NUTS classification

The NUTS classification is a hierarchical system developed by Eurostat for dividing the economic territory of the EU into regions. The NUTS system has three levels: NUTS 1, NUTS 2 and NUTS 3, representing progressively smaller geographical areas (see Figure 4).

At the broadest level, NUTS 1 corresponds to major socioeconomic regions, often comprising entire Member States or large regions within a Member State. Large administrative areas like North-West, Italy (ITC), or Bavaria, Germany (DE2), are examples of NUTS 1 regions.

The second level, NUTS 2, subdivides the NUTS 1 regions into smaller territorial units. NUTS 2 regions are often the basis for implementing regional policies and are particularly relevant for statistical analyses, including RESET. These regions typically align with administrative units such as provinces or regions. For example, in the figure, Swabia (DE27) represents a NUTS 2 region within Germany, illustrating a more granular level of geographical detail for policymaking and resource allocation. NUTS 2 data are widely used in EU cohesion policy to allocate funding and monitor regional economic performance.

At the most detailed level, NUTS 3 splits up NUTS 2 regions into even smaller units, often corresponding to districts, counties or other local administrative areas. For instance, Ostallgäu (DE27B) and Unterallgäu (DE27C) are NUTS 3 subregional areas within the DE27 region shown in the figure. This level of granularity provides highly localised information and supports targeted policy interventions and regional development strategies. However, NUTS-3-level data are much less available than NUTS 2 data, making NUTS 2 the most disaggregated level available for use in RESET.

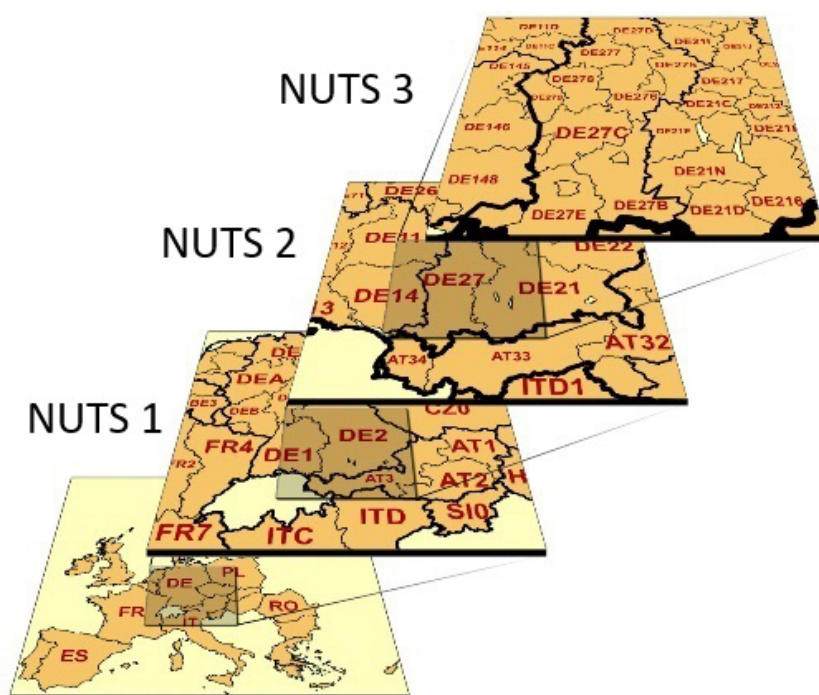
The NUTS classification system ensures consistency and comparability across the EU, making it an essential tool for regional analysis, planning and the distribution of structural funds. It has three guiding principles. First, it aligns with the administrative

⁽⁴⁾ For this reason, alternative regional classifications were also considered during the development process of RESET; see Annex 1 for details.

divisions of the 27 Member States to ensure practical data availability and effective policy implementation. Second, it maintains population size comparability by setting minimum and maximum population limits for each NUTS level. Last, by ensuring stability over time, it facilitates consistent and reliable longitudinal data analysis.

Source: Eurostat, 2026.

Figure 4. **NUTS classification**



Source: Eurostat 2024 (edited).

While international databases and specialised research platforms offer valuable data, they often do not meet the NUTS-2-level requirement. As a result, Eurostat de facto becomes the primary data source because it provides harmonised, high-quality and regionally disaggregated statistics for all Member States.

However, even in the extensive [Eurostat database](#), there are significant gaps. Many datasets do not have comprehensive coverage for all NUTS 2 regions, limiting their usefulness for detailed regional analysis. These gaps can result from variations in data collection methods, reporting standards or the availability of data across different sectors.

Despite these limitations, Eurostat remains a vital source for regional data due to its standardised approach and the broad scope of information it provides. The challenge, therefore, is selecting and integrating the most reliable and complete datasets to ensure the robustness and comprehensiveness of RESET. Specific

extractions from the [Labour Force Survey](#) (LFS) were also requested directly from Eurostat to complement the publicly available regional data ⁽⁵⁾. This made it possible to include in RESET indicators that had not previously been examined and presented at the regional level, which increases the added value of this innovative index.

Alongside Eurostat-based indicators, additional indicators were included from data sourced from Cedefop's skills online vacancy analysis tool for Europe (Skills-OVATE) (Cedefop, 2026d), the European Quality of Government Index (EQI) (Charron et al., 2022, 2024) and the European Tertiary Education Register (ETER) Project (2026), which is part of the [European Higher Education Sector Observatory](#).

In total, more than 150 indicators were collected for a total of 244 NUTS 2 regions.

3.2.4. Selected indicators

As outlined in Section 3.1, RESET has four pillars: skills supply, skills demand, skills environment and skills match. Each pillar represents a crucial dimension for understanding regional skills ecosystems and is further broken down into sub-pillars and specific indicators (see Figure 5).

- (a) **Skills supply.** This pillar captures the availability and development of skills in a region. It has two sub-pillars: 'skills formation', which encompasses indicators related to education and training systems and their capacity to produce skilled workers, and 'labour attraction', which measures the extent to which regions attract and retain a qualified workforce. The rationale is that these features will assess the production of skills via formal learning pathways and the capacity to draw talent into the region.
- (b) **Skills demand.** This pillar reflects skills requirements in the economy. Skills demand has two sub-pillars. This first sub-pillar is 'employment and productivity', which captures workforce participation and productivity levels. It captures the quantity of demand (how many jobs), how many people are being demanded to produce units of output (particularly in the high-skill area) and productivity. The second sub-pillar is 'employment tasks', which examines the specific tasks required in European jobs. It includes the nature of demand, that is, what is done in jobs. Jointly, these sub-pillars provide a comprehensive image of how skills are demanded and used in the regional skills ecosystems.
- (c) **Skills environment.** This pillar assesses contextual factors that influence skills ecosystems. It has three sub-pillars: the 'quality of the education

⁽⁵⁾ We wish to thank Eurostat for their continuous support to this project through numerous data extractions.

environment', which evaluates institutional quality, inclusion and fairness; the 'quality of the business environment', which captures the level of development in economic activity; and 'education–business cooperation', which measures the strength of linkages between education and training providers and the business sector. Collectively, these sub-pillars describe the enabling environment for skills development and utilisation.

- (d) **Skills match.** This pillar highlights skills mismatches and barriers to effective skills utilisation. It features two sub-pillars: 'labour market imbalances', which examines mismatches between skills supply and demand, and 'activity and transition', which focuses on activity rates and the transition of young people from education or training to the labour market. This pillar is crucial for identifying where regional skills ecosystems fall short in balancing skills availability and use.

Figure 5. Index structure with details

RESET			
Pillar	Pillar	Pillar	Pillar
SKILLS SUPPLY	SKILLS DEMAND	SKILLS ENVIRONMENT	SKILLS MATCH
Sub-pillar	Sub-pillar	Sub-pillar	Sub-pillar
Skills formation	Employment and productivity	Quality of education environment	Labour market imbalances
Adults with a learning experience all / sec	Employment in hi-tech sectors	Quality of public education	Macroeconomic skills mismatch
Basic digital technology knowledge	Labour productivity	Equal treatment in education	Labour market slack
Higher education attainment	Compensation of employees	Integrity issues in public education	Unemployment all / IVET
Student population	Green pervasiveness	Sub-pillar Quality of business environment	Long-term unemployment all / sec
NEET	Scientists and engineers	Working from home	Sub-pillar Activity and transition
Sub-pillar Labour attraction	Highly skilled employed people	Business sophistication	Activity of young persons all / IVET
Attraction of foreign higher education graduates	Sub-pillar Employment tasks	Sub-pillar Education-business cooperation	Activity of adult persons all / IVET
Net migration	Cognitive tasks all / IVET	Higher education co-publications with industry	Employment of young graduates all / IVET
	Digital technology all / IVET	Higher education-business cooperation (EU projects)	
all / IVET Available for all and only IVET graduates		all / sec Available for all and only secondary education graduates	

NB: IVET = initial vocational education and training; NEET = young people not in education, employment or training; sec = secondary education graduates.

Source: Cedefop.

Table 1 provides a structured overview of RESET, including the nature of the expected contribution of indicators to the overall index (+ or –), and their rationale and policy relevance (for more details on indicators, see Table 11 in Annex 4).

Table 1. **Index structure with expected contribution and policy relevance**

Pillar	Sub-pillar (code)	Indicator name (code)	Expected contribution	Rationale and policy relevance
Skills supply	Skills formation (SkillFor)	Student population (studworkage)	+	Captures the future pipeline of skilled labour.
		NEET (neet)	–	Highlights disengaged youth requiring policy intervention.
		Higher education attainment (he_att)	+	Indicates availability of advanced skills supporting innovation and growth.
		Basic digital technology knowledge (dig_never)	+	Reflects readiness for digital transformation in the workforce.
		Adults with a learning experience (all/SEC) (cvet_all / cvet_sec)	+	Promotes continuous skills development and adaptability to changing labour market demands.
	Labour attraction (LabAttr)	Attraction of foreign higher education graduates (hegrad_forattr)	+	Supports talent inflow and helps address skills shortages.
		Net migration (netmig_5y)	+	Indicates capacity to attract and retain population and workforce.
Skills demand	Employment and productivity (EmpProd)	Employment in hi-tech sectors (htc_emp)	+	Signals demand for advanced technological skills.
		Labour productivity (labprod_nom_hw)	+	Core determinant of economic performance and competitiveness.
		Compensation of employees (compemp_workage)	+	Reflects labour market value creation and remuneration conditions.
		Green pervasiveness (oja_grpe)	+	Indicates how far green skills requirements spread across jobs.
		Scientists and engineers (hrst_se)	+	Measures the strength of the technical and innovation-oriented workforce.

Pillar	Sub-pillar (code)	Indicator name (code)	Expected contribution	Rationale and policy relevance
	Employment tasks (TaskEmpl)	Highly skilled employed people (highskill_emp)	+	Reflects demand for advanced qualifications in employment.
		Cognitive tasks (all/IVET) (cog_task_all / cog_task_ivet)	+	Indicates prevalence of analytical and problem-solving tasks.
		Digital technology (all/IVET) (dig_task_all / dig_task_ivet)	+	Reflects use of digital tools in work and alignment with modern job requirements.
Skills environment	Quality of education environment (EduEnv)	Quality of public education (qog_qualedu)	+	Determines the effectiveness of human capital formation.
		Equal treatment in education (qog_eqtreatedu)	+	Reflects inclusiveness and fairness in education systems.
		Integrity issues in public education (qog_corrededu)	–	Undermines governance quality and efficiency in education.
	Quality of business environment (BizEnv)	Working from home (work_home)	+	Reflects organisational flexibility and digital readiness.
		Business sophistication (secemp)	+	Indicates the sophistication of economic activities.
	Education–business cooperation (EduCoop)	Higher education co-publications with industry (pub_partcomp)	+	Measures collaboration between academia and firms.
		Higher education–business cooperation (EU projects) (eufp_partcomp)	+	Reflects participation in innovation and knowledge transfer networks.
Skills match	Labour market imbalances (Lablmb)	Macroeconomic skills mismatch (smi)	–	Reflects systemic mismatch between skills supply and demand.
		Labour market slack (slack)	–	Indicates underutilised labour resources.
		Unemployment (all/IVET) (unemp_all / unemp_ivet)	–	Measures difficulties in labour market integration.
		Long-term unemployment (all/SEC) (unemplong_all / unemplong_sec)	–	Signals persistent structural labour market issues.
	Activity and transition (ActTrans)	Activity of young persons (all/IVET) (act_you_all / act_you_ivet)	+	Measures labour force participation of young people.

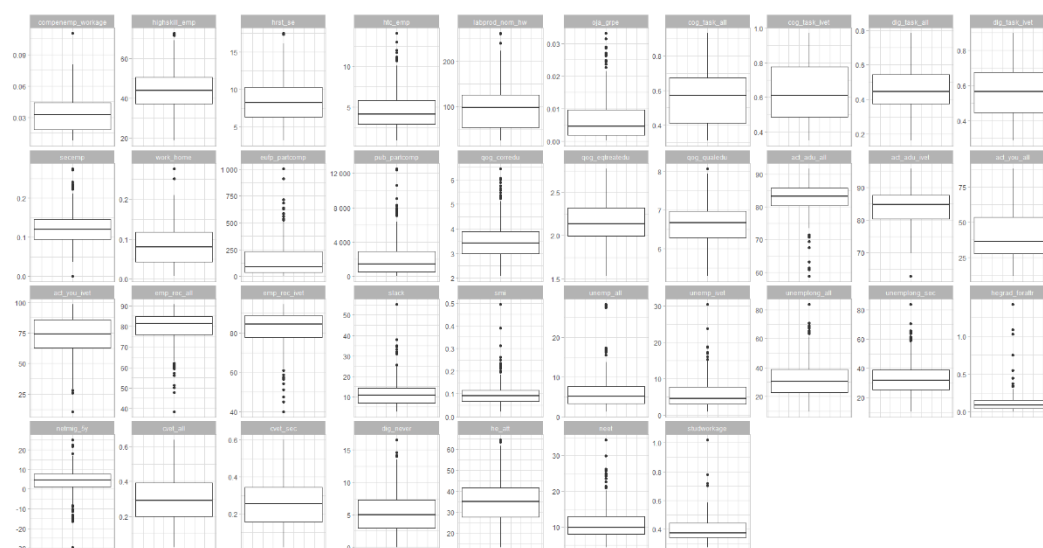
Pillar	Sub-pillar (code)	Indicator name (code)	Expected contribution	Rationale and policy relevance
		Activity of adult persons (all/IVET) (act_adu_all / act_adu_ivet)	+	Measures labour force participation among adults.
		Employment of young graduates (all/IVET) (emp_rec_all / emp_rec_ivet)	+	Indicates effectiveness of the school-to-work transition.

Source: Cedefop.

3.2.5. Merging indicators

Once the indicators were selected, the data preparation process started by sequentially merging multiple datasets into a single master file. The next step focused on filtering and cleaning the regional data to ensure accuracy and relevance. Regions with non-standard codes, which typically represent placeholders or incomplete data, were systematically removed. Similarly, countries or regions that fall outside the scope of the analysis, such as Switzerland or the United Kingdom, were excluded.

The cleaning process also involves eliminating redundant and unnecessary variables, such as labels, frequencies and auxiliary classifications that do not contribute to the core analysis. Variables with excessive missing values, such as duplicated employment indicators or inconsistent survey measures, were systematically removed to streamline the dataset. The resulting indicators were then systematically harmonised and structured so that the dataset is comprehensive, robust and aligned with the requirements of further analytical steps.

Figure 6. **RESET indicator distributions**

Source: Cedefop.

Figure 6 shows the distribution of selected indicators using box plots, highlighting key characteristics such as spread, central tendency and the presence of outliers ⁽⁶⁾.

The quality of an indicator is determined by its relevance, soundness and comparability. In this case, the box plots reveal asymmetrical distributions and extreme values for several indicators, which may affect their statistical coherence. Outliers, shown as isolated points outside the whiskers, can distort aggregate measures if not addressed, as they deviate significantly from the core distribution. Indicators with extreme skewness or large tails may also compromise robustness during aggregation or normalisation processes.

The presence of such distributions suggests the need for data treatment methods to improve indicator quality.

3.3. Data treatment

3.3.1. Missing data

After preparing the raw data, the common issue of missing values, which is typical when working with regional datasets across multiple indicators and time periods,

⁽⁶⁾ These and all following analyses were originally run with all collected indicators, but in this research paper only the variables included in the final dataset are shown. for reasons of simplification, comprehensibility and readability.

was addressed ⁽⁷⁾. Missing data can lead to information loss and imbalance in variable contributions.

To minimise these impacts, a two-stage imputation strategy has been applied ⁽⁸⁾. This sequential hot deck approach aligns with [JRC and OECD guidelines for composite indicator construction](#), which recommend combining temporal proximity with geographical similarity when imputing missing data.

First, temporal imputation addresses missing values by carrying forward the most recent available observation within each region. This last observation carried forward (LOCF) method assumes relative stability in indicators over time, making it particularly effective for slowly evolving measures such as population growth or educational attainment. However, this approach only fills forward in time and cannot address gaps where no historical data exist for a region. The approach implements a five-year maximum gap constraint (as recommended by the JRC COIN team during a dedicated COIN open day in October 2025).

Second, spatial imputation fills remaining gaps by leveraging geographical relationships. For each missing value at the NUTS 2 level, the median across all other NUTS 2 regions within the same NUTS 1 administrative area is calculated and used as an estimate ⁽⁹⁾. The median is chosen over the mean to minimise the

⁽⁷⁾ All following steps are performed with the help of the COINr package in R (Becker et al., 2022). Some more advanced analyses required additional coding to achieve their thorough implementation.

⁽⁸⁾ We include Member-State-level and EU-aggregate observations alongside NUTS 2 regions throughout the entire analysis pipeline, which is defensible on both statistical and practical grounds. Member State values are population-weighted averages of their constituent regions, which means they are inherently smoothed towards the centre of the cross-sectional distribution and virtually never sit at the tails. They therefore do not trigger winsorisation thresholds, do not shift kurtosis or skewness statistics in any meaningful way and do not redefine the min–max bounds used in normalisation. In the rare instances where a Member State value slightly exceeds the regional range (e.g. due to missing values for some regions), the resulting normalised score marginally exceeds the nominal upper bound, which is both transparent and informative rather than distorting. Processing all units through every stage of the pipeline, including robustness checks such as Monte Carlo simulations over alternative weighting schemes and aggregation rules, ensures that the confidence intervals and rank stability measures reported for Member States and regions are estimated under identical assumptions and are mutually consistent. This avoids the need for post hoc replay of transformations under separately estimated parameters, which would introduce their own inconsistencies for non-linearly treated indicators and complicate the interpretation of sensitivity results. This approach seems also to have been followed by other indices like the 2025 Regional Innovation Scoreboard (European Commission, 2026b). See Annex 5 for a list of all included regions.

⁽⁹⁾ Note that regional information is only available at the NUTS 1 level for Germany for two variables and for Greece for one variable (see Annex 2 for details). In these cases, we opted for copying the NUTS 1 values to the corresponding NUTS 2 regions.

influence of outliers, providing robust estimates that reflect typical regional patterns. This peer-based approach maintains geographical coherence while ensuring comprehensive coverage across all regions.

This two-stage methodology balances temporal trends with spatial patterns, enabling fair comparisons across regions while maintaining methodological rigour. More advanced methods could theoretically be employed but do not add real value in the context of RESET (see Annex 2 for details).

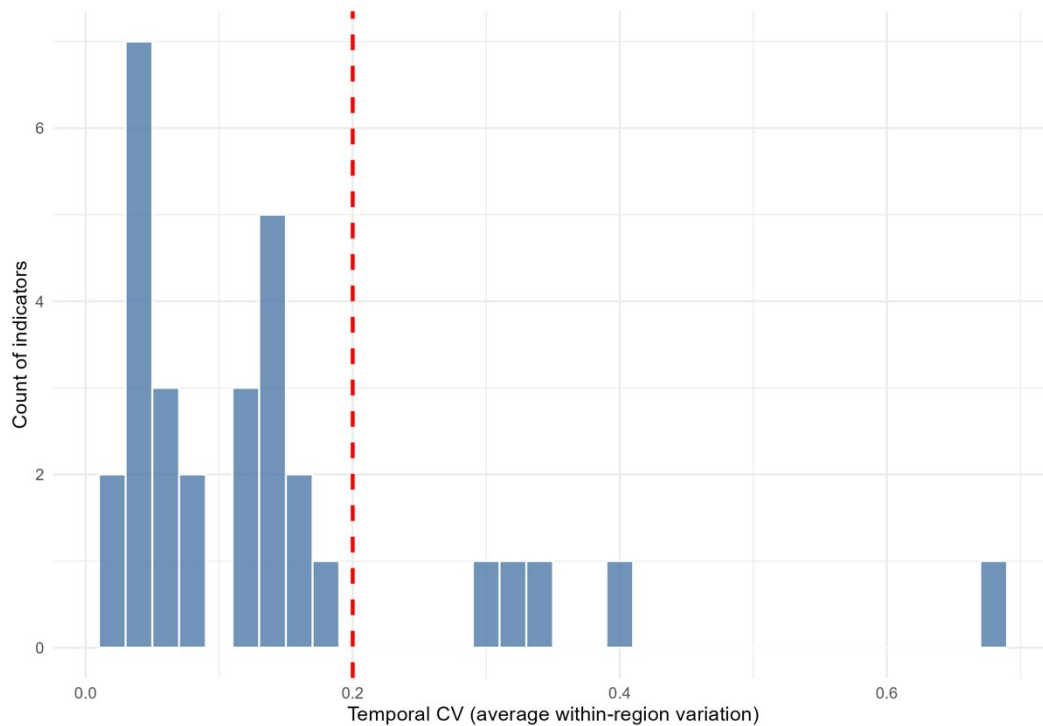
3.3.2. Temporary volatility assessment

Prior to applying temporal imputation to the 2024 reference year (the most recent year with a high level of data coverage as of March 2026), a systematic assessment of indicator volatility was conducted to evaluate the appropriateness of the LOCF method. The coefficient of variation (CV), calculated as the standard deviation divided by the mean of each indicator's values within regions over time, is the primary metric for temporal stability.

As there is no established cut-off for determining when carry-forward imputation is acceptable in longitudinal socioeconomic indicators, the screening threshold was treated as an operational choice. The boundary was set at a temporal CV of 20 % to flag indicators with a large year-to-year variation relative to their mean. The threshold is used as a diagnostic screen to identify indicators warranting closer scrutiny, not as proof that LOCF is unbiased below that value. LOCF imputation is applied uniformly across all indicators; the volatility classification serves to flag cases where the carried-forward values may introduce greater distortion and where results should be interpreted with additional caution.

Figure 7 presents the distribution of temporal volatility across all indicators. The majority of the indicators exhibit low temporal volatility, with values clustering below the 20 % threshold, suggesting the appropriateness of this threshold. This distribution confirms that LOCF imputation is methodologically appropriate for the bulk of the indicator set, as most measures evolve gradually over time within regions.

Figure 7. **Distribution of temporal volatility of RESET indicators**



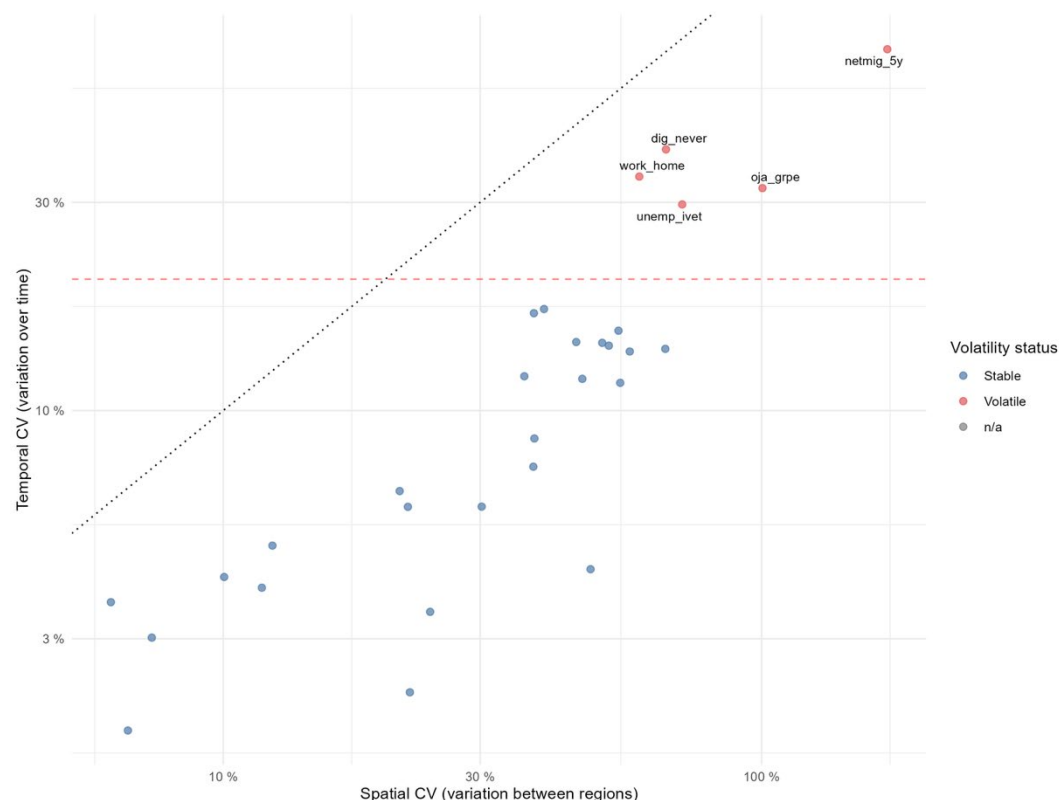
NB: The red dashed line marks the 20 % temporal CV threshold used to assess indicator stability for LOCF imputation; indicators to the left of the line are considered sufficiently stable for LOCF, while indicators to the right are considered volatile and warrant closer review.

Source: Cedefop.

Figure 8 examines the relationship between spatial variation (differences across regions) and temporal variation (changes over time)⁽¹⁰⁾. Indicators positioned in the lower-right quadrant exhibit high spatial heterogeneity but low temporal volatility; these represent structural characteristics that differ substantially between regions but remain stable over time, making them ideal candidates for temporal imputation. The five indicators exceeding the 20 % temporal CV threshold are labelled and merit closer examination.

⁽¹⁰⁾ See the Annex 4 for details on the years included for all indicators.

Figure 8. **Spatial versus temporal variation of RESET indicators**



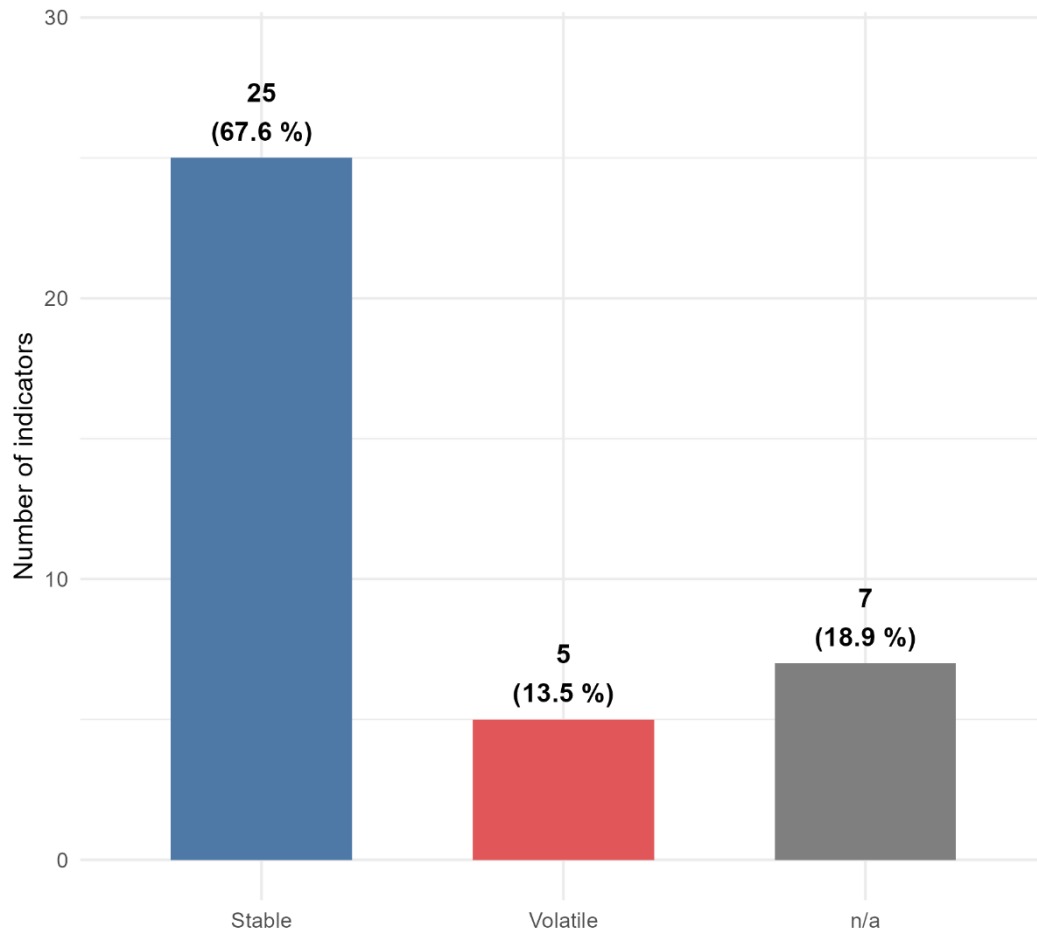
NB: n/a = not applicable. Each point represents an indicator, plotted on logarithmic scales. The diagonal dotted line indicates equal spatial and temporal variation. Indicators above the horizontal red dashed line (20 % temporal CV) are classified as volatile.

Source: Cedefop.

Figure 9 summarises the volatility classification results. Of the 37 RESET indicators ⁽¹¹⁾, 25 (67.6 %) were classified as stable, while only 5 (13.5 %) exceeded the volatility threshold. A further seven indicators could not be assessed due to insufficient temporal observations (i.e. the data were available for less than three years).

⁽¹¹⁾ Some indicators have been entered twice for different subpopulations, that is, for all graduates and for IVET or secondary graduates only.

Figure 9. **Indicator volatility classification of RESET indicators**



Source: Cedefop.

Detailed examination of the five volatile indicators reveals that their higher volatility does not compromise the imputation strategy. Since the composite index is constructed for a single reference year (2024) rather than for time-series comparison, the primary concern with LOCF imputation, namely, systematic bias from carrying forward outdated values across multiple years, does not apply. For the 2024 reference year, all five volatile indicators have data available for most regions:

- (a) 'net migration' (temporal CV = 67.3 %, with data from 2022 onwards);
- (b) 'basic digital technology knowledge' (CV = 39.7 %, with data from 2018);
- (c) 'working from home' (CV = 34.4 %, with data from 2019);
- (d) 'green pervasiveness' (CV = 32.3 %, with data from 2020); and
- (e) 'unemployment (IVET)' (CV = 29.7 %, with data from 2019).

While most regions have 2024 observations, a small number require carrying forward values by up to four years (notably for 'working from home' and

‘unemployment (IVET)’), and the five-year-gap limit applied during imputation prevents the use of excessively outdated values.

Consequently, temporal imputation for these indicators typically involves carrying forward values by one or two years for most regions, though a small subset of regions may require longer carry-forward periods of up to four years. As the index will be extended to future reference years, each edition will similarly draw on contemporaneous data. This helps ensure that the volatility observed in historical patterns does not affect cross-sectional regional comparisons within any given year ⁽¹²⁾.

Figure 10 provides additional context by classifying the RESET indicators according to their response to the COVID-19 pandemic. The classification is based on changes in mean values relative to the 2019 baseline (where available):

- (a) ‘stable’ denotes indicators where year-over-year changes remained within $\pm 5\%$ in both 2020 and 2021;
- (b) ‘dip’ indicates a decline exceeding 10 % in 2020 and 5 % in 2021;
- (c) ‘spike’ indicates a corresponding increase above those thresholds;
- (d) ‘mixed’ captures indicators with heterogeneous responses that do not fit the other categories; and
- (e) ‘none’ indicates that no 2019 baseline was available to assess impact, typically because the indicator’s time series begins after 2019.

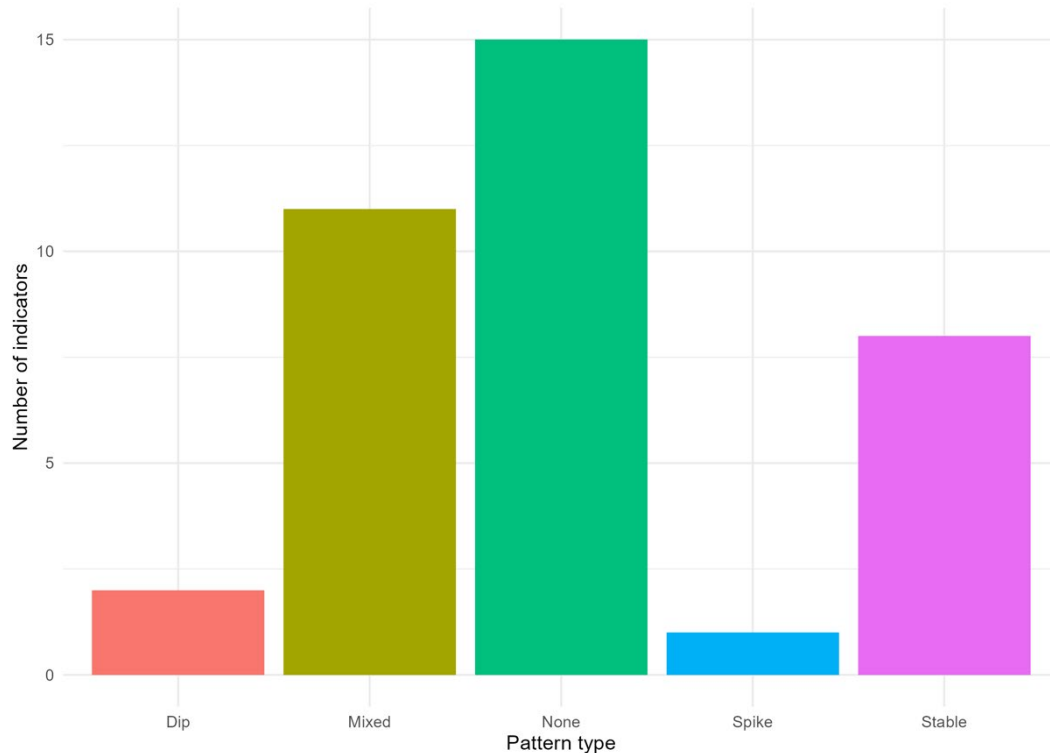
Of the 37 RESET indicators, 15 (40.5 %) are classified as ‘none’ due to the absence of pre-pandemic data, and 8 (21.6 %) remained ‘stable’ throughout the pandemic period, together accounting for nearly two thirds of the indicator set. Among the remaining indicators, 11 (29.7 %) show ‘mixed’ patterns with heterogeneous changes across 2020 and 2021. Only three indicators display a clear directional COVID-19 impact: ‘long-term unemployment (all)’ ⁽¹³⁾ and ‘basic digital technology knowledge’ experienced a pandemic ‘dip’, while ‘working from home’ showed a pronounced ‘spike’ (nearly doubling in 2020 relative to 2019). These patterns are consistent with known impacts of economic disruptions and the shift to remote working during the pandemic, and they are no reason to be concerned about data quality. The predominance of stable and unaffected

⁽¹²⁾ The indicators of the ‘employment tasks’ sub-pillar are currently only available for 2022, as they are part of a Eurostat ad hoc module. However, we argue that these task shares are typically fairly stable over time, so that the data also provide meaningful insights for the years after 2022. In addition, future ad hoc modules may update these data.

⁽¹³⁾ The apparent dip in ‘long-term unemployment (all)’ reflects a compositional effect: the surge in short-term unemployment during 2020 mechanically reduced the long-term share, rather than indicating an improvement in long-term unemployment outcomes.

indicators supports the choice of temporal imputation methods for the composite index.

Figure 10. **COVID-19 impact patterns of RESET indicators**



NB: Classification based on percentage change in mean indicator values relative to the 2019 baseline: 'stable' ($\pm 5\%$ in both 2020 and 2021), 'dip' (decline $> 10\%$ in 2020 and $> 5\%$ in 2021), 'spike' (increase $> 10\%$ in 2020 and $> 5\%$ in 2021), 'mixed' (other patterns), 'none' (no pre-pandemic baseline available).

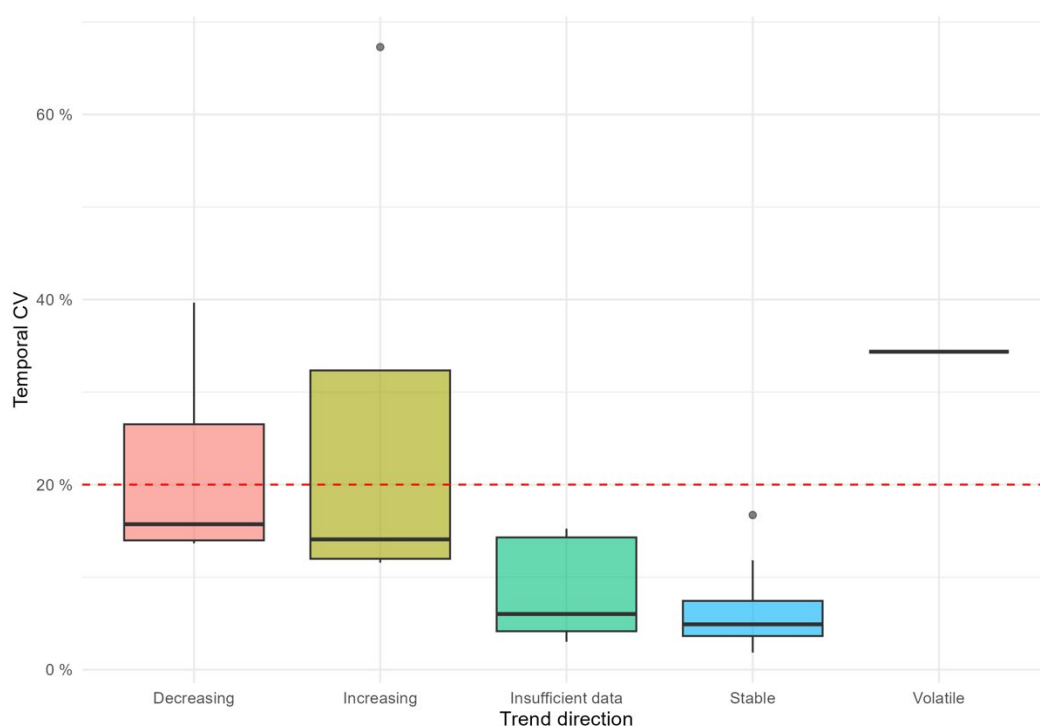
Source: Cedefop.

Figure 11 illustrates the relationship between trend direction and temporal volatility. Trend direction is classified by fitting a linear regression of each indicator's cross-regional mean on time, with the slope expressed as a percentage of the overall mean. Indicators with a normalised slope exceeding 3% are classified as 'increasing', those below -3% as 'decreasing' and those within $\pm 3\%$ as 'stable', provided they also have a temporal CV below 20% . Indicators within the $\pm 3\%$ slope range but exceeding the 20% CV threshold are classified as 'volatile', that is, exhibiting no consistent directional trend but substantial year-to-year fluctuation.

Where fewer than three yearly observations are available, trend estimation is not attempted, and the indicator is labelled 'insufficient data'. As expected, indicators classified as 'stable' exhibit the lowest temporal CVs, with a median of 4.9% and all values below the 20% threshold. Those with 'increasing' or

‘decreasing’ trends show higher median CVs and wider dispersion, reflecting the fact that systematic directional change over time mechanically inflates within-region variation. Both categories contain outliers above the 20 % threshold: ‘net migration’ (67.3 %) and ‘green pervasiveness’ (32.3 %) among increasing indicators, and ‘basic digital technology knowledge’ (39.7 %) and ‘unemployment (IVET)’ (29.7 %) among decreasing ones. The single indicator classified as ‘volatile’ is ‘working from home’ (34.4 %), which showed no consistent directional trend but substantial year-to-year fluctuation driven by the COVID-19 pandemic. Indicators with insufficient temporal data for trend classification cluster at low CV values (median 6.0 %), though this reflects their short time series (typically only two or three observations), which limits the reliability of the CV estimate itself.

Figure 11. **Volatility by trend direction and RESET indicator category**



NB: Trend direction is determined by the normalised slope of a linear time trend ($> 3\%$ = increasing, $< -3\%$ = decreasing, within $\pm 3\%$ = stable or volatile depending on CV). The red dashed line indicates the 20 % CV threshold. Each box shows the median and interquartile range; individual points represent outliers.

Source: Cedefop.

In summary, the temporal volatility assessment confirms that the two-stage imputation strategy is methodologically sound. Of the 37 RESET indicators, 25 (67.6 %) exhibit sufficient temporal stability for LOCF imputation, while 7 could not be assessed due to short time series. Among the five volatile indicators, the large majority of regions have 2024 data, though a small number require carry-forward

periods of up to four years (notably for ‘working from home’ and ‘unemployment (IVET)’), and some regions lack data entirely for these indicators; these cases are addressed by the second imputation stage (median of NUTS 1 group) rather than by LOCF. While alternative imputation methods (e.g. using the mean of NUTS 1 group or k -nearest neighbours (k -NN)) are possible, they have a negligible value added (see Section 3.8 on robustness and sensitivity for more details).

3.3.3. Outliers

Outliers, defined as extreme values that deviate markedly from the rest of the data, play a dual role in data analysis. They can signal exceptional performances or reveal large measurement errors. However, their presence poses significant challenges to statistical analysis, as they can bias descriptive statistics, disrupt statistical coherence and distort normalisation steps. To address this issue, detecting and treating outliers is a critical part of preparing data for robust analysis. The outlier treatment strategy employed in RESET follows a systematic multi-step approach. Importantly, each indicator receives only one transformation: the first treatment pass that successfully brings it within acceptable thresholds. This ensures that indicators are not over-treated, preserving their authentic characteristics while achieving the necessary statistical coherence for composite index construction.

The treatment methodology is guided by two key statistical measures, as recommended by the JRC and OECD guidelines (Nardo et al., 2008; European Commission, 2023a): skewness, which captures the asymmetry of distributions, and kurtosis, which measures the presence of heavy tails or peaked centres. Indicators are assessed against established thresholds ($|\text{skewness}| \leq 2.0$ and $\text{kurtosis} \leq 3.5$) that define acceptable statistical properties for composite index construction. These thresholds ensure that all indicators contribute to the final index on comparable statistical footings, preventing any single indicator from unduly influencing results due to distributional anomalies. The choice of these thresholds balances the need for statistical normality with the practical reality that (close to) perfectly normal distributions are rare in socioeconomic data.

The first treatment stage employs a conservative strategy. This initial stage applies a two-step sequential process to all indicators that exceed the established thresholds. First, winsorisation is attempted, which caps extreme values by replacing the most extreme data points with the next most extreme non-outlier value. It ensures that treatment remains conservative, adjusting only the five most problematic outlying observations while preserving the rank order and overall character of the data. Unlike percentile-based approaches, this method directly

limits the number of observations modified, ensuring that no more than a small proportion of extreme values are adjusted.

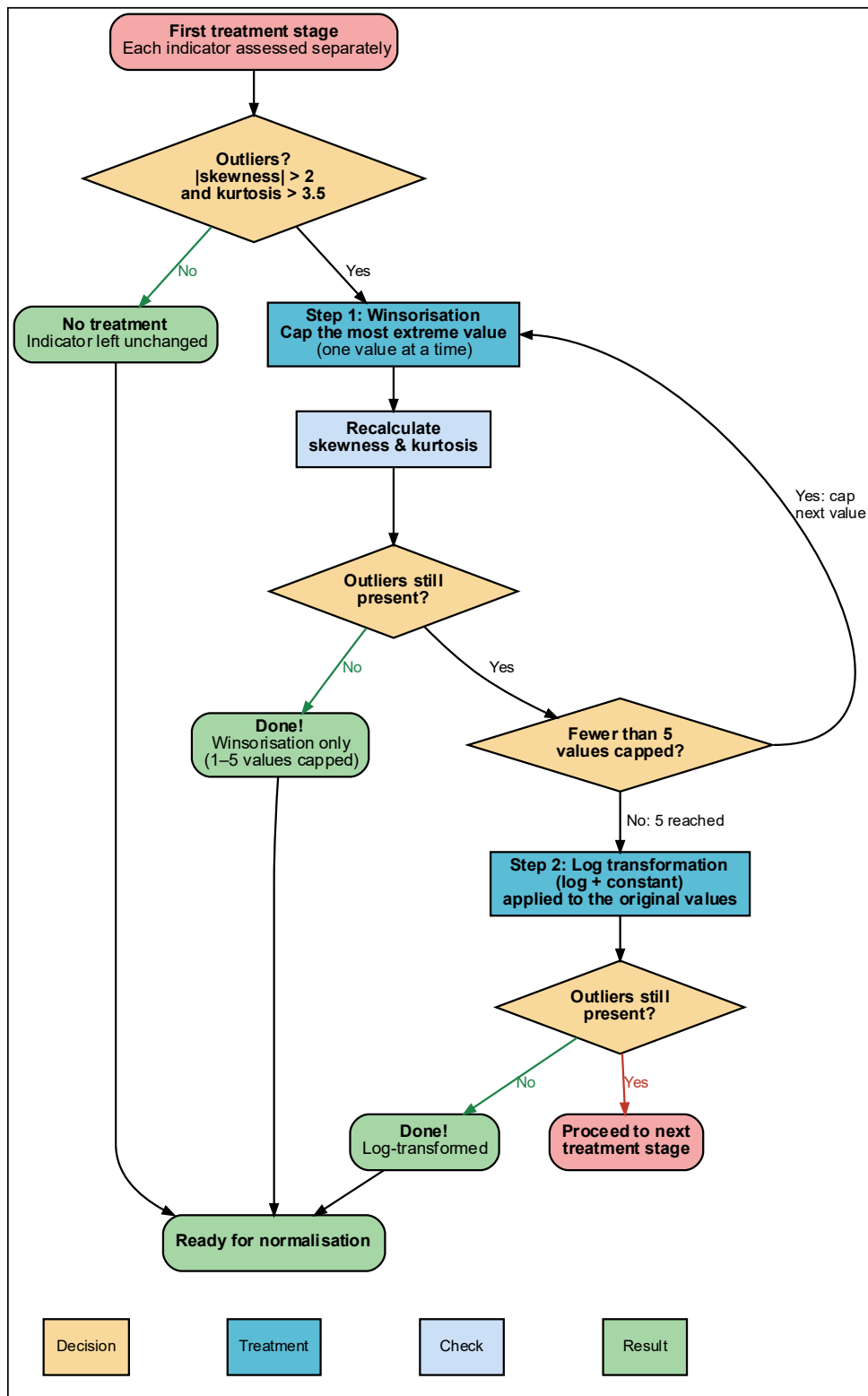
For indicators that remain statistically problematic after winsorisation, as assessed by recalculating skewness and kurtosis, a logarithmic transformation is instead applied to the entire distribution. This transformation is particularly effective for indicators with strong positive skew, as it compresses large values more than small values, effectively pulling extreme outliers closer to the bulk of the distribution. The logarithmic transformation fundamentally rescales the data, making it more suitable for subsequent normalisation and aggregation steps while maintaining the relative ordering of observations.

This conservative approach prioritises minimal intervention, addressing only the most severe distributional issues using techniques that are well established in the statistical literature. By attempting winsorisation before logarithmic transformation, the methodology preserves the original scale and interpretation of indicators wherever possible.

Further treatment stages would adopt a more aggressive, tailored approach for indicators that remain problematic after first-stage treatment. They include treatments including more aggressive winsorisation, Box–Cox and other transformations ⁽¹⁴⁾.

⁽¹⁴⁾ Box–Cox transformations are a ‘parametric way to nonlinearly transform a set of points with the aim of making their distribution approximately Gaussian’ (Bicego and Baldo, 2016, p. 390).

Figure 12. Treatment decision tree used for RESET indicators



Source: Cedefop.

The decision tree (Figure 12) showcases how indicators are routed through treatment paths based on their characteristics: indicators without outliers are left unchanged, indicators with outliers are winsorised one value at a time until the outlier criterion is no longer met (up to five values), and indicators that still show outliers after five capped values are log-transformed instead (using their original values). The decision tree structure ensures that each indicator receives the treatment that is appropriate to its unique distributional properties, maximising the probability of successful treatment while maintaining data integrity. In case the thresholds are not passed after these two steps, then further steps are employed (see Annex 3).

The multi-step treatment methodology described above was applied to the 37 RESET indicators retained after the indicator removal process. Prior to treatment, 32 of the 37 retained indicators (86.5 %) already satisfied the established thresholds ($|\text{skewness}| \leq 2.0$, $\text{kurtosis} \leq 3.5$) without any intervention. The remaining five indicators (13.5%) exhibited distributional properties that exceeded both thresholds and required treatment (Table 2).

Table 2. **Kurtosis and skewness improvements for all treated RESET indicators**

Indicator	Initial kurtosis	Final kurtosis	Initial skewness	Final skewness
Attraction of foreign higher education graduates	26.44	0.47	4.68	0.16
Macroeconomic skills mismatch	16.21	5.31	2.99	1.79
Student population	11.16	3.80	2.28	1.48
Unemployment (all)	9.68	1.90	2.47	1.37
Labour market slack	8.19	3.55	2.15	1.60

Source: Cedefop.

Among the problematic indicators, kurtosis values ranged from moderately above the threshold (8.19 for 'labour market slack') to substantially elevated levels (26.44 for 'attraction of foreign higher education graduates'). Other indicators with notable excess kurtosis included 'macroeconomic skills mismatch' (16.21), 'student population' (11.16) and 'unemployment (all)' (9.68). Skewness values were always higher than the threshold, from the highest (4.68 for 'attraction of foreign higher education graduates') to the lowest (2.15 for 'labour market slack') among these indicators.

The first treatment step, employing standard winsorisation, capping the most extreme values, successfully resolved four of the five initially problematic

indicators, raising the overall pass rate from 86.5 % to 97.3 %. The indicators successfully treated at this step were 'macroeconomic skills mismatch', for which kurtosis and skewness were reduced from 16.21 to 5.31 and from 2.99 to 1.79, respectively, 'student population' (11.16 to 3.80; 2.28 to 1.48), 'unemployment (all)' (9.68 to 1.90 and 2.47 to 1.37) and 'labour market slack' (8.19 to 3.55 and 2.15 to 1.60).

One indicator remained above skewness and kurtosis thresholds after Step-1. The indicator remaining problematic was 'attraction of foreign higher education graduates'. This indicator exhibited strong positive skew, making it well-suited to the logarithmic transformation approach employed in this pass. This transformation reduced the kurtosis and skewness from 26.44 to 0.47 and from 4.68 to 0.16, respectively. The second treatment step resolved the problems for all five remaining variables, raising the overall pass rate to 100 %.

Table 3 presents the cumulative treatment results across all steps, illustrating the progressive resolution of distributional issues through the multistep pipeline.

Table 3. **Cumulative treatment results across all passes of problematic RESET indicators**

Step	Indicators passing	Pass rate (%)	Fixed in this step
Initial assessment	32/37	86.5	—
After Step-1	36/37	97.3	4, using winsorisation
After Step-2	37/37	100.0	1, using logarithmic transformation

Source: Cedefop.

The complete resolution of all distributional issues within two steps confirms the effectiveness of the treatment strategy for the RESET indicator set. It further confirms that the RESET indicator set exhibits distributional characteristics that are amenable to established treatment techniques. The absence of any residual cases eliminates the need for threshold exceptions or alternative treatment strategies.

These results of the treatment procedures provide a robust statistical foundation for the subsequent stages of composite indicator construction. All indicators now exhibit distributional properties that are fully compatible with the normalisation and aggregation methods to be applied, ensuring that the final composite index reflects genuine regional variation rather than artefacts reflecting distributional anomalies.

3.4. Normalisation

Normalisation is a critical step in constructing composite indicators, as it transforms different indicators to a common scale, ensuring their comparability. Without normalisation, indicators measured in different units or scales cannot be meaningfully aggregated. Proper normalisation ensures that each indicator contributes appropriately to the composite measure, preserving the integrity and interpretability of the final score.

Normalisation methods are available for different types of data and objectives. The choice of normalisation method depends on the specific properties of the data and the objectives of the composite indicator.

For RESET, indicators have been normalised using the min–max method. This approach standardises values between 1 and 100, ensuring that higher values consistently reflect more favourable outcomes. For instance, employment rates are scaled so that 100 represents the best-performing region, while 1 reflects the lowest-performing region. Such standardisation ensures that all indicators are measured on the same scale, making aggregation meaningful and straightforward.

The use of min–max normalisation in RESET is particularly advantageous, as it preserves relative distances between values, allowing for a clear comparison across regions. This method also aligns well with the wide range of indicator types used in the index. By combining robust outlier treatment with consistent normalisation, this step guarantees that all indicators, regardless of their original scales or distributions, contribute fairly and proportionately to the final index.

Figure 13. **RESET** indicators after normalisation

Figure 13 presents the results of normalising indicators, with each plot representing the distribution of an indicator after applying the min–max normalisation method. The figure demonstrates that normalisation standardises indicator scales and reduces bias caused by differences in variability or magnitude, enabling equitable contributions of all indicators to the composite index.

3.5. Weighting

Weighting involves assigning relative importance to each indicator, reflecting their contribution to the overall measure. One type of method for weighting is equal weighting, where all indicators are assigned the same weight. This method has been used for the first round of RESET (see the robustness section for alternative weightings and the justification of this method of choice) ⁽¹⁵⁾.

3.6. Aggregation

RESET is constructed using a hierarchical aggregation process that aligns with the structure of the index. At the base level, normalised indicators are combined into thematic sub-pillars that reflect specific aspects of the regional skills ecosystem, such as skills formation, employment and productivity. These sub-pillars are then aggregated to form the RESET pillars that capture the key dimensions of the index: skills supply, skills demand, skills environment and skills match. Finally, these pillars are combined to produce the aggregate RESET score, providing a single, interpretable measure of regional performance.

The aggregation process uses the arithmetic mean, which assumes equal importance for all indicators within a group. This method is transparent and straightforward and helps ensure that no single component dominates the results. By weighting indicators equally within their respective groups, the arithmetic mean reflects the collective contribution of all components, while still allowing the structure of the index to reveal which pillars or sub-pillars drive regional performance. The hierarchical approach provides a clear framework for

⁽¹⁵⁾ Note that RESET contains deliberately paired indicators that measure the same underlying construct for different populations, that is, indicators capturing a variable for VET or secondary graduates and all graduates. In these cases, each variant is assigned a weight of 0.5, reflecting the fact that together they represent a single conceptual dimension. This prevents any one construct from exerting disproportionate influence on the composite score simply because it is observed across multiple population groups, while still preserving the analytical and policy value of the disaggregation.

interpreting the index, as users can examine results at the indicator, sub-pillar, pillar and aggregate levels to identify regional strengths and weaknesses.

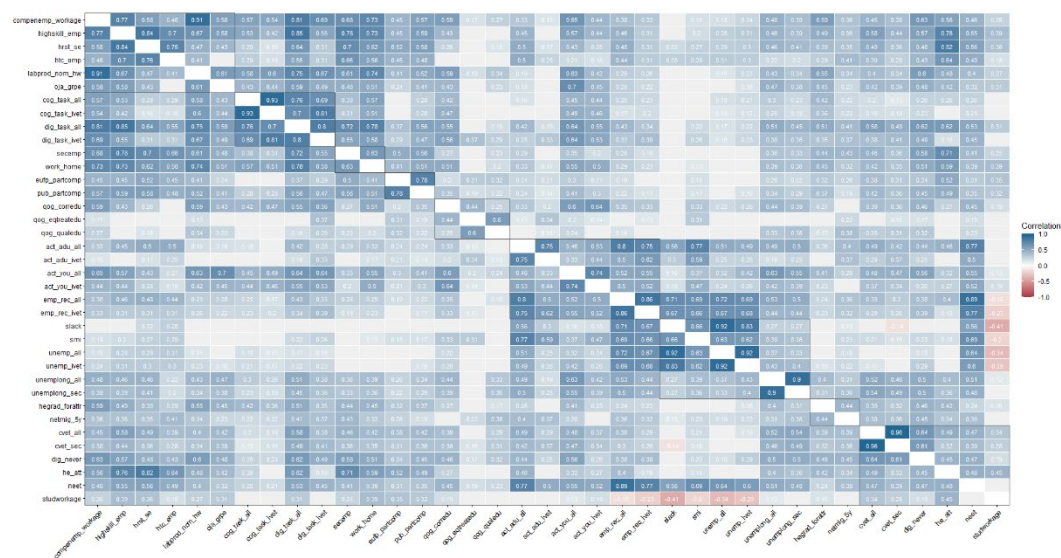
3.7. Statistical coherence

Statistical coherence is a crucial aspect of constructing and validating composite indicators. It involves ensuring that the various components of the indicator are internally consistent and accurately represent the underlying phenomenon. This concept is essential for the credibility and reliability of composite measures. In developing RESET, correlation and reliability analysis were carried out.

3.7.1. Correlation analysis

Correlation analysis is the first step in assessing statistical coherence. This method examines the relationships between different indicators within the composite framework. By calculating correlation coefficients, we can determine the degree to which two variables are linearly related. A perfect positive correlation (1) indicates that the variables move together, while a perfect negative correlation (-1) indicates they move in opposite directions. No linear correlation (0) suggests no relationship. Correlation analysis helps identify whether indicators are allocated correctly within the framework, if some are under- or over-represented, and up to what level aggregation should occur.

Figure 14. **Correlation matrix of RESET indicators, showing all correlations**



Source: Cedefop.

The full correlation matrix (Figure 14) provides a comprehensive overview of the relationships between the various indicators in RESET. The patterns reveal

clusters of high correlations among indicators belonging to similar conceptual domains. For example, 'labour market slack' and 'unemployment (all)' correlate at 0.92, confirming that they capture closely related phenomena ⁽¹⁶⁾. Although the two indicators are closely related and very highly correlated, they remain conceptually distinct enough for both to add value and therefore to be retained in RESET. As the JRC notes (European Commission, 2023a), '[t]he analysis of correlation alone is not the final source of every decision'.

Similarly, the continuing vocational training indicators 'adult with a learning experience (all)' and 'adult with a learning experience (secondary)' show a very high correlation of 0.96, and the long-term unemployment pair 'long-term unemployment (all)' and 'long-term unemployment (secondary)' correlate at 0.90. Among demand-side indicators, 'compensation of employees' and 'labour productivity' are strongly correlated at 0.91, and 'highly skilled employed people' shows consistently high correlations with 'scientists and engineers' (0.84), 'business sophistication' (0.78) and 'compensation of employees' (0.77).

Some of the highest correlations occur between indicator pairs that measure the same concept for different population groups – such as 'unemployment (all)' and 'unemployment (IVET)' (0.92) or 'cognitive tasks (IVET)' and 'cognitive tasks (all)' (0.93) – which is expected, as these variants capture the same underlying phenomenon for overlapping populations. To prevent over-representation of concepts measured by such population–variant pairs, each indicator within the pair receives a weight of 0.5 rather than 1 during aggregation, ensuring that the pair contributes the equivalent of a single indicator to its dimension.

The indicator 'NEET' shows high correlations with 'employment of young graduates (all)' (0.89) and 'activity of adult persons (all)' (0.77), but more moderate correlations with other indicators in its pillar such as 'adult with a learning experience (all)' (0.47) and 'higher education graduates' (0.48). 'NEET' has been kept in its pillar for conceptual reasons, as it captures a failure at the point of skills formation (i.e. young people who are neither acquiring skills through education and training nor building them through employment) and thus measures a gap in the pipeline that feeds the labour market. This is conceptually a supply-side deficiency, even though its consequences manifest as matching outcomes that strongly correlate with other demand-side and matching indicators.

⁽¹⁶⁾ According to Eurostat (2026), unemployment is a part of labour market slack. More precisely, the latter 'refers to all unmet needs for employment. It includes unemployment as defined by the EU Labour Force Survey (EU-LFS) and the following 3 groups: Underemployed part-time workers; People seeking a job but not immediately available to work; People available to work but not seeking'.

A small number of negative correlations are also visible, most notably ‘student population’, which correlates negatively, for example with ‘labour market slack’ (–0.41), ‘unemployment (all)’ (–0.34) and ‘unemployment (IVET)’ (–0.29). However, these indicators are not positioned in the same pillar. ‘Student population’ captures the breadth of a region’s engagement with skills formation across the entire education system. Its negative correlation with slack and unemployment rates is structurally expected: regions with high levels of student enrolment tend to have larger shares of their working-age population still completing initial education or engaged in upskilling and retraining. As these people often enter or re-enter the labour market upon completion, they temporarily inflate regional unemployment during the transition.

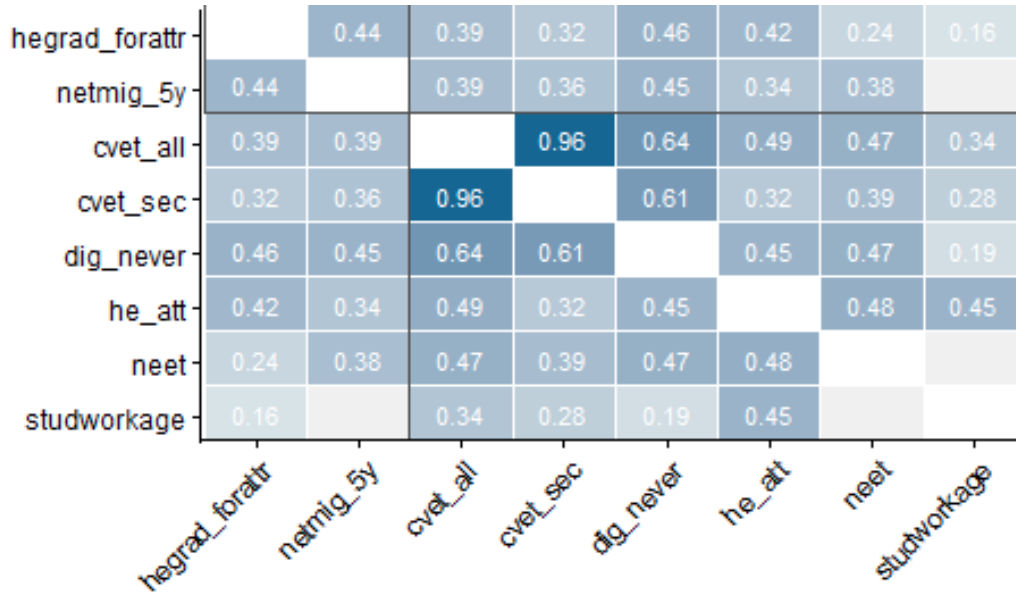
The negative correlation reflects the natural friction between education participation and labour market absorption rather than a genuine deficiency in the skills ecosystem. Despite the low or negative correlations, the indicator has been retained because it measures a fundamental input to the skills ecosystem. Without including an indicator of the scale of skills formation activity relative to the working-age population base, the index would lack a direct measure of how intensively a region invests in developing human capital at all levels.

According to the JRC COIN guidelines, all indicators that are aggregated should have a correlation of at least 0.30, as a sufficient correlation between indicators facilitates the flow of information from indicators to aggregates by ensuring that they point in the same direction and provide non-conflicting information. RESET has 37 indicators, yielding 614 non-null unique indicator pairs. Of these, 425 (69 %) meet the guideline of at least 0.30, indicating a broadly coherent correlation structure⁽¹⁷⁾. The remaining 183 pairs (30 %) have correlations between 0.10 and 0.30, suggesting weak but still positive relationships rather than complete independence. Importantly, no pair has a correlation near zero (below 0.10 in absolute value), meaning no pair provides entirely unrelated information. Only six pairs (1 %) exhibit negative correlations, all involving the indicator ‘student population’, and all but one are cross-pillar. The overall correlation structure is thus coherent and supports aggregation.

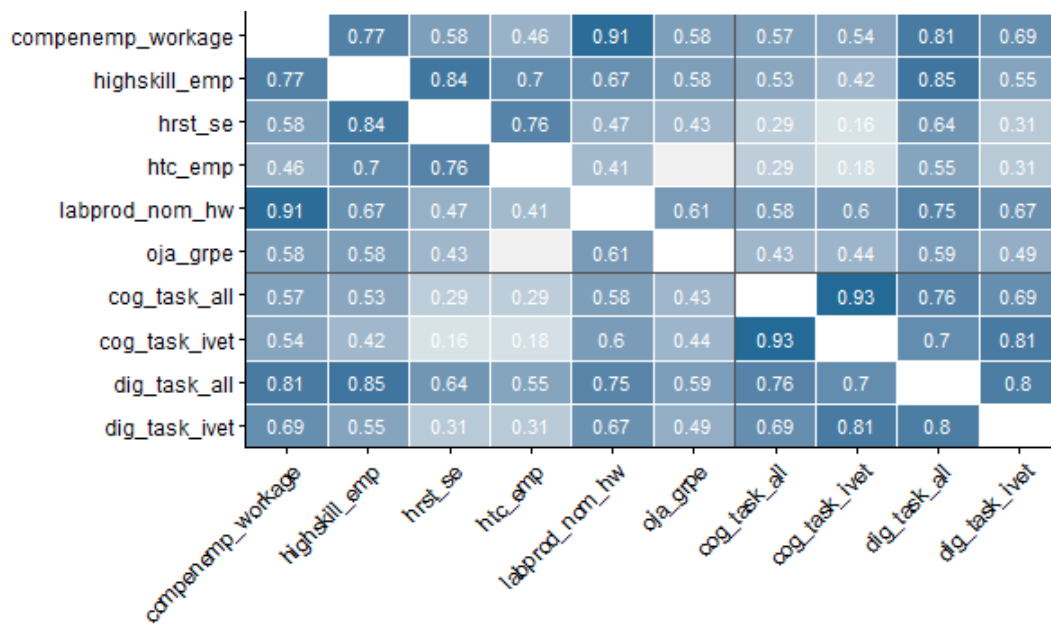
⁽¹⁷⁾ To put these numbers into context, the JRC audit of the Regional Innovation Scoreboard reported that 60 % of indicator pairs met the 0.30 threshold, which was considered ‘a good result given the large number of correlations’ among its 23 indicators (Smallenbroek et al., 2025, p. 63). The overall statistical coherence of the Regional Innovation Scoreboard was assessed as excellent (Smallenbroek et al., 2025).

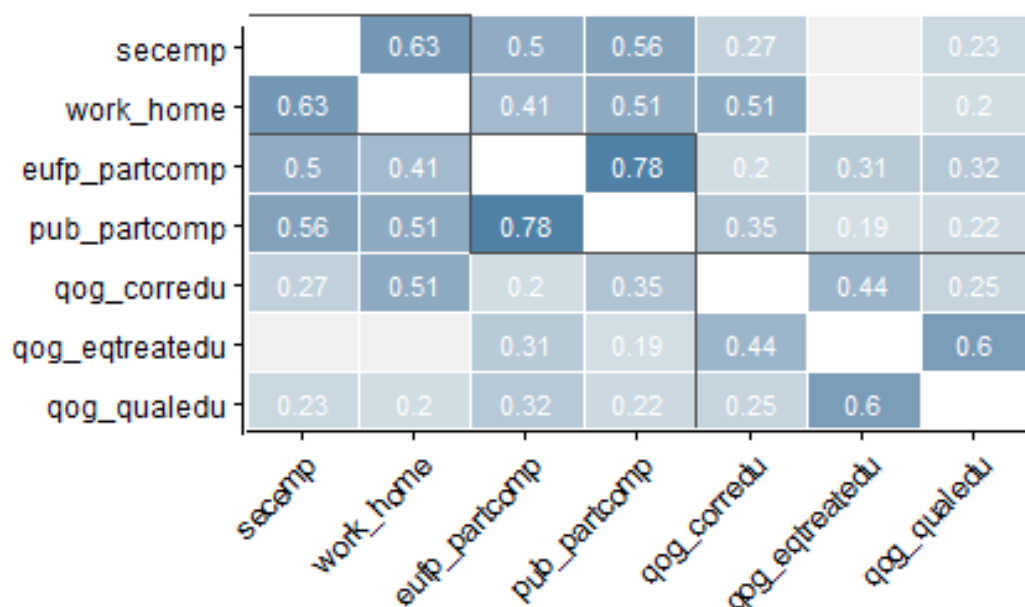
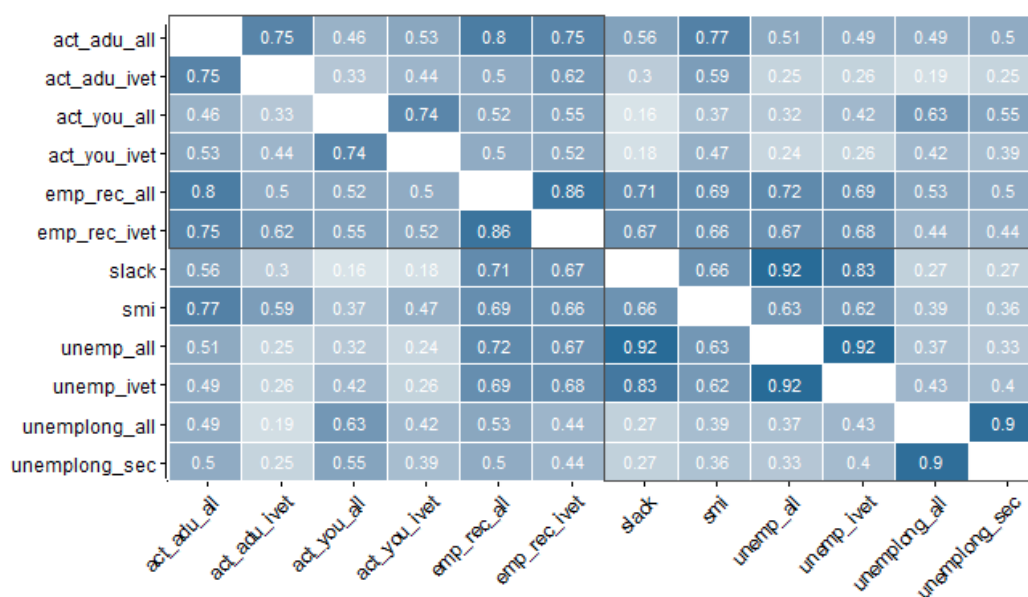
Figure 15. **Correlation matrix of RESET indicators, only showing within-pillar correlations**

Skills supply



Skills demand



Skills environment**Skills match**

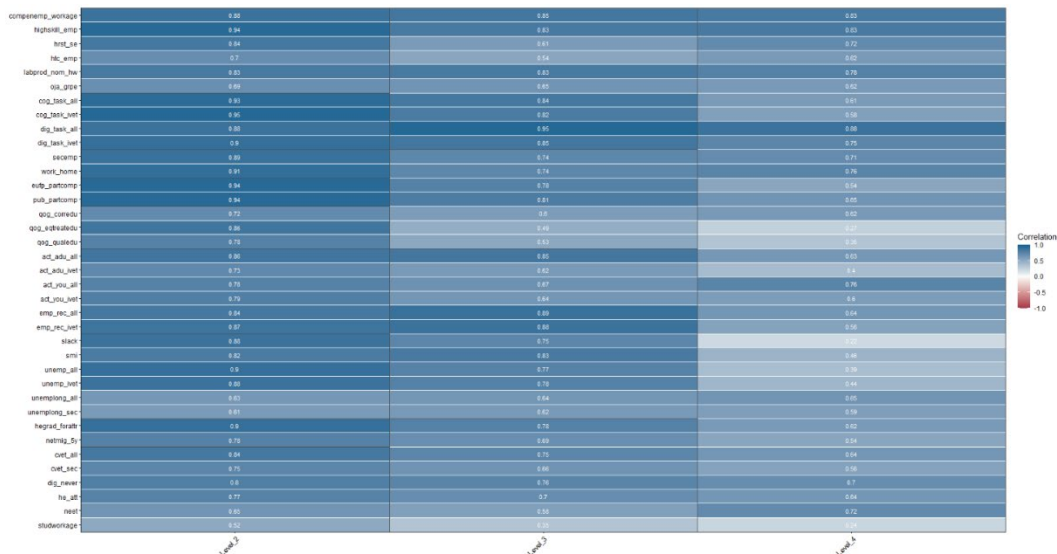
Source: Cedefop.

The correlation matrix of the indicators within pillars as shown in Figure 15 indicates the same but more clearly shows the blocks of indicators grouped into sub-pillars (surrounded by a black line). (High) positive correlations within each block confirm the internal coherence of indicators allocated to the same dimension.

The two correlation matrices offer distinct insights into the relationships between indicators and their grouping structures within the RESET framework. The

second matrix aggregates correlations at the level of parent groupings, providing a more focused lens on internal consistency within designated groups. Conversely, the first matrix offers a comprehensive view of correlations across all indicators, allowing for a broader comparison of relationships between variables.

Figure 16. **Correlation matrix of RESET indicators with parent levels**



Source: Cedefop.

The correlation matrix in Figure 16 offers a detailed view of how individual indicators align with their sub-pillar, their pillar and the index, providing valuable insights into the coherence and robustness of RESET's structure. A significant number of indicators exhibit strong positive correlations with their parent dimensions, underscoring their validity and importance within the framework.

However, a few indicators demonstrate moderate to lower correlations with their parent levels. At the index level, 'labour market slack' shows the weakest correlation (0.22), followed by 'student population' (0.24), 'equal treatment in public education system' (0.27) and 'quality of public education' (0.35).

At the pillar level, 'student population' (0.35), 'equal treatment in public education system' (0.49), 'quality of public education' (0.53) and 'employment in hi-tech sectors' (0.54) stand out as the lowest. These weaker correlations are not necessarily problematic – they may indicate that these indicators capture distinct aspects of the phenomenon that are not fully reflected in the broader aggregate. For instance, the quality-of-government indicators measure institutional features that vary largely at the national level, which may explain their weaker alignment with a predominantly regional index. 'Labour market slack' correlates well with its sub-pillar (0.88) and pillar (0.75) but weakly with the overall index, suggesting that

the dimension it belongs to contributes distinct rather than overlapping information to the composite. In such cases, the decision to retain or adjust indicators is guided by conceptual relevance rather than statistical fit alone.

Assessed against the JRC COIN guideline of a minimum 0.30 correlation between indicators and the index, the good correlation structure between indicators is well reflected in the correlations between indicators and RESET: 34 of the 37 indicators (92 %) meet this threshold at the index level, and 29 (78 %) exceed 0.50, demonstrating that the information from the indicators is well reflected in the index ⁽¹⁸⁾. Correlation between indicators and the index is below 0.30 for three indicators: ‘labour market slack’ (0.22), ‘student population’ (0.24) and ‘equal treatment in public education system’ (0.27). As discussed above, all three have conceptual justifications for their retention. ‘Labour market slack’ correlates well with its own sub-pillar (0.88) and pillar (0.75), contributing distinct information. ‘Student population’ correlates moderately with its sub-pillar (0.52) and captures a dimension that does not scale linearly with the overall index. ‘Equal treatment in public education system’ captures institutional features that may vary less at the regional than the national level.

The correlation of five indicators with the index is in the 0.30–0.50 range: ‘quality of public education’ (0.35), ‘unemployment (all)’ (0.39), ‘activity of adult persons (IVET)’ (0.40), ‘unemployment (IVET)’ (0.44) and ‘macroeconomic skills mismatch’ (0.46). These moderate correlations do not pose issues, as these indicators are close to or above the acceptable threshold and their information is still sufficiently reflected in the overall index scores.

The correlation matrix reaffirms the structural soundness of RESET, with most indicators demonstrating strong alignment with their parent dimensions.

Table 4. **Correlation of RESET pillars with aggregate index**

Pillar	Correlation with index
Skills supply	0.86
Skills demand	0.89
Skills environment	0.84
Skills match	0.69

Source: Cedefop.

⁽¹⁸⁾ To put these numbers into context, the JRC audit of the Regional Innovation Scoreboard reported that 83 % of indicators correlated with the overall index at 0.30 or above. The overall statistical coherence of the Regional Innovation Scoreboard was assessed as excellent (Smallenbroek et al., 2025).

The correlation matrix between RESET and its four pillars (Table 4) provides additional significant insights into how well these components align with the aggregate index and contribute to its measurement. It is not necessary for all pillars to have the same correlation with the aggregate index. Variations in correlations are expected and can reflect the nature and importance of the dimensions being measured. For instance, certain pillars may inherently capture more critical aspects of the concept, leading to stronger correlations. This is consistent with the idea that the significance of each pillar varies depending on the phenomenon the index aims to represent.

The differences in correlations also stem from the conceptual framework of the index. Skills supply, skills demand and skills environment all measure absolute levels, namely the stock of skills available, the intensity of demand for skills and the quality of the institutional environment. These level-based measures tend to be positively correlated because they reflect an underlying regional development gradient: regions with stronger economies tend to score higher on supply, demand and environmental quality simultaneously.

Skills match, by contrast, captures the degree of alignment across the supply, demand and environment dimensions, which is a relative concept that does not necessarily move in the same direction as the absolute levels of its constituent parts. A region can have both high supply and a strong environment yet still exhibit significant mismatches or, conversely, achieve good alignment at lower absolute levels. This conceptual distinction means that a lower correlation between the skills match pillar and the overall index is not a sign of weakness but rather indicates that this pillar captures genuinely distinct information that is not redundant with the other three dimensions.

From a methodological perspective, while equal weights are applied during the aggregation process, this does not imply that the correlations of all pillars with the index should be uniform. The observed range (from 0.69 for skills match to 0.89 for skills demand) is consistent with a framework where some pillars capture level effects that naturally co-vary, while others capture alignment dimensions that contribute complementary information. However, it remains important to ensure that no single pillar disproportionately drives the index or becomes under-represented.

3.7.2. Reliability analysis

Reliability analysis, particularly Cronbach's alpha, measures the internal consistency of the composite indicator. It evaluates the ratio of total covariance between indicators to the total variance, with higher values indicating better reliability. Cronbach's alpha values above 0.9 are considered excellent, while

values below 0.5 are unacceptable. Cronbach's alpha analysis ensures that the indicators consistently reflect the underlying construct that they are intended to measure.

The index demonstrates a very high level of internal consistency, as indicated by its Cronbach's alpha value of 0.95, confirming that the indicators included in the index are highly consistent and effectively measure a coherent construct. This result provides strong evidence that the RESET components work harmoniously to represent the underlying dimension of regional skills ecosystems and that the aggregate index is reliable.

While a high Cronbach's alpha is desirable, it is important to exercise caution in its interpretation. Cronbach's alpha tends to increase as the number of indicators rises. In cases where many indicators are included, even modest correlations between them can inflate the alpha value. For RESET, the very high value may suggest that some indicators provide overlapping or redundant information (e.g. the simultaneous inclusion of IVET and all graduates indicators) ⁽¹⁹⁾. This redundancy, while not necessarily detrimental to reliability, could reduce the efficiency of the index and its ability to represent distinct facets of the concept it measures.

3.8. Robustness and sensitivity analysis

3.8.1. Adjustments

To ensure the robustness and reliability of RESET, the methodology has incorporated systematic adjustment analyses. Adjustments include testing the impact of adding, removing or replacing indicators within the index structure. This helps identify indicators that are either redundant (due to their high correlation with other components or being less conceptually relevant) or insignificant, as they do not meaningfully contribute to the index's variation. By refining the selection of indicators, the analysis ensures that only the most relevant and impactful variables are retained, strengthening the overall reliability of the index.

The analysis started by including over 150 indicators, themselves reflecting a thorough process of finding and testing new indicators or generating others. Through an iterative process, in which several requirements had to be tested and met, such as the need to retain a balance between pillars, ultimately 37 indicators were retained following statistical and theoretical considerations.

⁽¹⁹⁾ It is important nevertheless to note that the effect of such overlapping indicators has also been considered by specifying a 0.5 weighting among them.

3.8.2. Uncertainty

Uncertainty analysis has been conducted using Monte Carlo simulations, where key assumptions, such as imputation methods, normalisation methods, weights and aggregation techniques, are varied systematically.

Monte Carlo simulation is a powerful technique used to understand the impact of risk and uncertainty in prediction and forecasting models. By running many simulations, each with varied inputs that reflect possible real-world variations, this method helps quantify the uncertainty in the composite indicator results. The method involves generating random samples of input variables and computing the composite indicator for each set of inputs, thus creating a distribution of possible outcomes. This distribution provides insights into the variability and robustness of the composite indicator, allowing for a more comprehensive understanding of potential deviations due to uncertainties in the input data and methodological choices.

Monte Carlo simulation provides insight into how assumptions impact index scores and rankings. Visualisations like uncertainty plots summarise the range of possible outcomes under different scenarios. It is important to carefully define the assumptions, as the method is computationally intensive, particularly with large datasets or many simulations, and the results depend heavily on the quality and relevance of the input distributions.

Table 5. **Methods used in uncertainty analysis for RESET**

Category	Method	Description	Pros	Cons
Imputation methods	NUTS 1 median, NUTS 1 mean, <i>k</i> -NN	Fills missing values using group-level statistics (median or mean of the NUTS 1 region) or <i>k</i> -NN within the same Member State.	Retains all observations; accounts for regional contexts; multiple methods allow robustness testing.	Group-based methods assume within-group homogeneity; <i>k</i> -NN requires sufficient Member-State-level observations.
Normalisation alternatives	Min–max normalisation	Scales data to a range (e.g. 1–100), ensuring uniform bounds across all indicators.	Preserves original data distribution; intuitive interpretation.	Sensitive to outliers; dependent on extreme values.

Category	Method	Description	Pros	Cons
	Shifted z-score normalisation	Standardises data based on mean and standard deviation (mean = 10, standard deviation = 2), then shifts all values so the minimum becomes 1, ensuring strict positivity.	Accounts for data distribution; reduces influence of scale discrepancies; the shift ensures compatibility with geometric mean aggregation.	Assumes normality; the shift alters the absolute scale, making cross-indicator levels less directly interpretable.
Weight perturbation	Noisy weights	Applies random perturbations to weights at specified levels using predefined noise factors.	Identifies sensitivity to weight variability; realistic representation of uncertainties.	Requires precise calibration of noise levels to reflect plausible scenarios.
Aggregation methods	Arithmetic mean	Aggregates indicators by summing and dividing by the count.	Simple, transparent, widely used.	Treats all indicators equally; sensitive to outliers.
	Geometric mean	Aggregates indicators by multiplying values and taking the n th root.	Penalises extreme values; emphasises relative changes.	Requires non-negative data; sensitive to zeros.
	Mixed (arithmetic + geometric)	Uses arithmetic mean at the first two aggregation levels and geometric mean only at the final level.	Combines transparency of arithmetic mean for sub-indices with penalising properties of geometric mean for overall score.	Still requires positive values at the final level; less conventional than pure approaches.

Source: Cedefop.

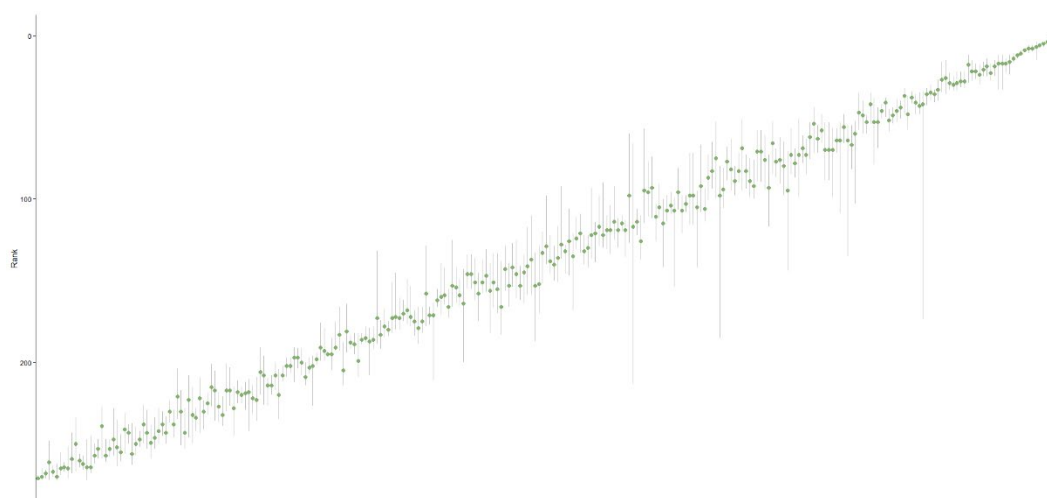
Imputation is used to fill missing indicator values so that all regions can be included in the composite index (Table 5). Three alternatives are tested: NUTS 1 median imputation, which replaces missing values with the median of the region's NUTS 1 group and serves as the baseline method; NUTS 1 mean imputation, which uses the group mean instead; and k -NN within the same Member State, which identifies the most similar regions based on available data to estimate missing values. Each method carries different assumptions about the structure of the data. Group-based methods (median and mean) assume that regions within the same NUTS 1 group are sufficiently homogeneous, while k -NN leverages

multivariate similarity but requires enough regions per Member State. Testing these three alternatives allows the uncertainty analysis to capture the effect of imputation choices on the final index rankings.

As for normalisation, min–max normalisation rescales all data to a predefined range of 1–100 (with the lower bound set to 1 rather than 0 to facilitate compatibility with the geometric mean), ensuring consistent bounds for all indicators. This method is simple, intuitive and widely used in composite indices, which is why it is the baseline RESET method. However, its sensitivity to outliers means extreme values can disproportionately affect the rescaling, which could lead to skewed results. As an alternative, a shifted z-score normalisation is used, which first standardises data based on a mean of 10 and standard deviation of 2, and then shifts all values so that the minimum becomes 1. This shift preserves the relative distances between all regions while guaranteeing strict positivity, which is required for geometric mean aggregation. The method assumes a normal distribution and is included in the analysis to assess the effect of this assumption on the index. While it reduces scale discrepancies, the shift alters the absolute scale, making cross-indicator levels less directly interpretable.

Weight perturbation introduces random variability into the assigned weights at specific levels, simulating uncertainties in stakeholder input or expert judgement. Our baseline weights were equal weights. This approach is particularly valuable for identifying components or indicators disproportionately influencing the index's outcomes. By applying predefined noise factors, the sensitivity of the index to weight variability is explored. The method requires careful calibration to ensure realistic representation of uncertainties without overstating their impact.

Finally, three alternative aggregation methods are tested. The arithmetic mean, which aggregates indicator values by summing and dividing by their count, serves as the baseline. Its simplicity and transparency make it a common choice in composite index construction. However, its equal treatment of all indicators may introduce biases, especially when data include outliers or indicators of varying importance. The geometric mean aggregates data by multiplying values and taking the n th root, emphasising proportional rather than absolute differences. This method inherently penalises extreme values, reducing the influence of outliers. Its requirement for strictly positive values is addressed by using a min–max range starting at 1 and a shifted z-score normalisation. In addition, a mixed approach is tested that applies the arithmetic mean at the first two aggregation levels and the geometric mean only at the final level, combining the transparency of the arithmetic mean for sub-indices with the penalising properties of the geometric mean for the overall index score.

Figure 17. **RESET uncertainty analysis (with $N = 6\,000$ replications)**

Source: Cedefop.

Figure 17 presents the outcome of a Monte Carlo uncertainty analysis with 6 000 replications for the regions in RESET ⁽²⁰⁾. Each green dot marks the median rank of a NUTS 2 region across replications, and the vertical bars show the 90 % confidence interval (from the 5th to the 95th percentile). Regions are ordered along the x-axis by their nominal ranking. Following JRC COIN guidelines (Smallenbroek et al., 2025), a shift of up to 15 % of the total ranking range (41 ranks) is considered acceptable, while shifts within 10 % (27 ranks) represent the expected level of stability.

The results indicate that RESET rankings are broadly stable under alternative modelling specifications. For 88 % of regions, the 90 % confidence interval remains within 41 ranks of the nominal position. A more stringent benchmark, that is, a shift of no more than 27 ranks (10 % of the range), is met by 68 % of regions. Notably, 30 % of regions display very tight confidence intervals of 14 ranks or fewer (5 % of the range), pointing to a high degree of ranking certainty at both ends of the distribution.

At the same time, 32 regions (12 %) exhibit confidence intervals exceeding 41 ranks. These are distributed across 15 Member States, with the largest contributions from Belgium (5 regions); Germany (4); and the Netherlands, Austria and Finland (3 each). The widest intervals belong to FI20 (Åland Islands, 147 ranks), NL23 (Flevoland, 140 ranks) and NL34 (Zeeland, 105 ranks). Regions ranked at the very top or bottom of the index tend to have narrower confidence

⁽²⁰⁾ The analysis is based on Monte Carlo simulations that vary all specified methodological assumptions jointly, rather than one at a time, to estimate the overall variability of results across alternative specifications.

intervals, suggesting that the extremes of the distribution are particularly robust to changes in methodology.

In conclusion, RESET demonstrates strong robustness to variations in key methodological assumptions. The analysis tested alternatives spanning imputation, normalisation, weight perturbation and aggregation. With 88 % of regional rankings remaining stable across a wide range of plausible methodological configurations, the index can be considered a reliable basis for cross-regional comparison.

3.8.3. Sensitivity

Building on uncertainty analysis, sensitivity analysis identifies the relative importance of assumptions in influencing index results. Variance decomposition methods quantify how much variability in index scores can be attributed to each assumption (Table 6). In this framework, noise is introduced at different levels of aggregation to highlight the impact of specific hierarchical decisions.

Both analyses test the same set of inputs (winsorisation, normalisation, weights and aggregation) and rely on Monte Carlo simulations, but they address fundamentally different questions. Uncertainty analysis asks how much total variability exists, producing distributional summaries of index scores and rankings across many alternative specifications. Sensitivity analysis asks which specific assumptions matter most, using variance-based global decomposition to rank each methodological choice by its contribution to overall output variability. The two approaches are therefore complementary. Uncertainty analysis establishes whether the index is sufficiently stable to support meaningful cross-regional comparisons. Sensitivity analysis identifies which assumptions analysts and policymakers should pay closest attention to when interpreting the results.

Table 6. **Characteristics of uncertainty and sensitivity analysis undertaken for RESET**

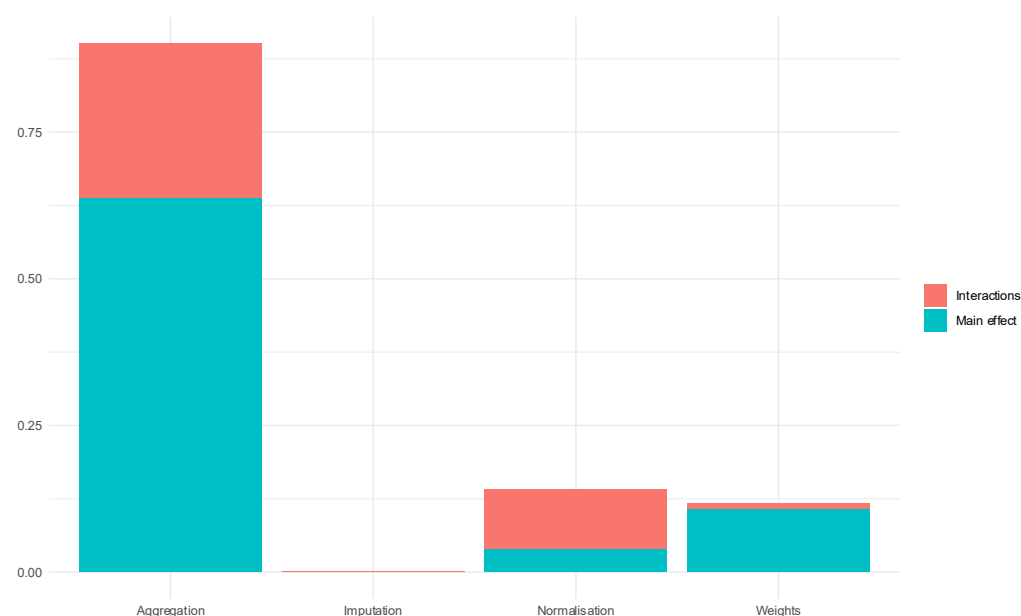
Aspect	Uncertainty analysis	Sensitivity analysis
Primary question	'How much variability is there due to input uncertainty?'	'Which factors contribute the most to variability?'
Objective	Quantify overall variability in outputs	Attribute variability to specific parameters

Aspect	Uncertainty analysis	Sensitivity analysis
Focus	Overall output variability	Contributions of individual parameters or methods
Inputs tested	Winsorisation, normalisation, weights, aggregation	Winsorisation, normalisation, weights, aggregation
Output	Variability distributions of results	Sensitivity indices ranking parameter influence
Implementation	Monte Carlo simulations of varied inputs	Variance-based global sensitivity analysis (also using Monte Carlo)

Source: Cedefop.

While sensitivity analysis identifies influential assumptions and guides methodological refinement, it is computationally demanding. Furthermore, it may not fully capture interactions between assumptions unless explicitly modelled. For instance, exploring the combined effects of varying weights and normalisation simultaneously may provide deeper insights but at the cost of increased complexity.

Figure 18. **RESET sensitivity analysis (with $N = 1\,000$ bootstrap replications), results 1**



Source: Cedefop.

Figure 18 decomposes the Sobol' sensitivity indices ⁽²¹⁾ into 'main effects' and 'interactions' for the four modelling assumptions varied in the analysis. Aggregation is by far the largest contributor to overall uncertainty, with a first-order Sobol' index (S_i) of 0.64 and a total-order Sobol' index (ST_i) of 0.90, meaning it accounts for roughly 64 % of variance independently and 90 % when interactions with other assumptions are included. Normalisation and weights each play a secondary role: normalisation has an S_i of 0.04 but an ST_i of 0.14, and weights has an S_i of 0.11 with an ST_i of 0.12. This indicates that in the case of normalisation, their independent effects are small but their influence roughly triples when interactions, primarily with the aggregation method, are considered. In the case of weights, the effect is predominantly direct.

Imputation shows negligible impact ($S_i \approx 0.000$, $ST_i \approx 0.001$), which is consistent with the fact that only 0.5 % of data cells are affected by (spatial) imputation; that is, the three methods tested (NUTS 1 median, NUTS 1 mean and k -NN) produce similar fill values for the small number of missing observations. This confirms that RESET is robust to the choice of imputation method, and that the dominant source of methodological sensitivity is the aggregation method, since switching between arithmetic and geometric means fundamentally changes how compensability operates across indicators.

⁽²¹⁾ They decompose 'the total variance of model output into additive terms, which represent the sensitivity effects ... [and] represent the amount of the total output uncertainty due to each input, solely or by interaction with the others' (Azzini et al., 2020).

Figure 19. **RESET sensitivity analysis (with $N = 1\,000$ bootstrap replications), results 2**

NB: 90 % confidence intervals shown.

Source: Cedefop.

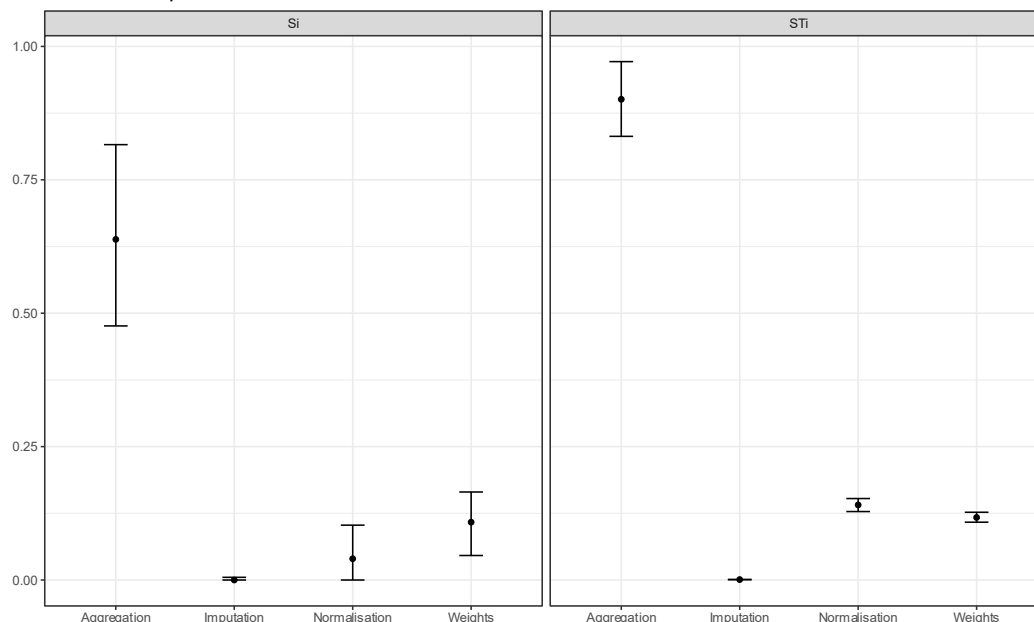


Figure 19 presents the Si and STi sensitivity indices separately. In the left panel, aggregation has the highest first-order index, confirming it explains the largest share of output variance independently. Normalisation and weights have much smaller independent effects, while imputation shows virtually no independent contribution. The right panel displays the total-order indices, which capture both direct effects and all interactions. Aggregation retains its dominance, and the gap between its Si and STi values indicates that a substantial part of its influence operates through interactions with normalisation and weight choices.

Normalisation shows markedly higher total effects than first-order effects, confirming that their influence is largely mediated through interactions with the aggregation method rather than being exercised independently. Weights have almost identical first-order and total effects, indicating their direct effect. The total effects of imputation remain negligible. The Sobol' decomposition analysis reinforces the conclusion that the choice of aggregation method is the decisive methodological assumption for RESET, while normalisation and weights play secondary roles and imputation has no meaningful impact on the results.

This is not unexpected, since aggregation directly determines how trade-offs across indicators and components are resolved, and therefore has a decisive influence on the meaning of the final index score. In RESET, the arithmetic mean was retained because it provides the most transparent and interpretable approach and is consistent with standard practice in composite indicator construction. While

alternative methods could have reduced compensability, they would also have imposed stronger assumptions about how imbalances across dimensions should be penalised. The influence of aggregation was therefore not minimised by changing its conceptual role but addressed by testing alternative aggregation methods and retaining the option judged to provide the clearest and most balanced representation of regional performance.

3.8.4. Principal component analysis

Following the uncertainty and sensitivity analyses, which examined the robustness of RESET to methodological choices, principal component analysis (PCA) was used to assess the statistical coherence of the index structure itself. While the previous analyses focused on how methodological assumptions affect index variability and rankings, PCA examines the extent to which indicators within each component measure a common underlying construct.

PCA is a multivariate statistical technique that identifies underlying dimensions capturing the variance within groups of indicators. By examining how much variance the first principal component (PC1) explains, we can assess the internal coherence of indicator groupings. High PC1 values indicate strong internal coherence, suggesting that indicators move together and capture similar aspects of the phenomenon being measured. This analysis is particularly valuable after establishing methodological robustness, as it helps confirm whether the theoretical and conceptual groupings of indicators are also statistically justified.

The potential benefits of incorporating PCA into the RESET development process must be assessed in relation to the correlation and reliability analysis, and in relation to the uncertainty and sensitivity analysis, already implemented (Table 7). Each of these methods offers distinct insights into the robustness and coherence of the index, and PCA has the potential to complement and strengthen them. From the perspective of correlation analysis, PCA goes beyond pairwise relationships by identifying broader latent structures in the data and highlighting clusters of indicators that contribute to the same underlying dimension. In doing so, it can help detect redundancy among highly correlated indicators and provide an additional statistical justification for indicator selection or adjustment.

In relation to reliability analysis, PCA can enrich the interpretation of internal consistency. While measures such as Cronbach's alpha indicate whether indicators within a component are consistent with one another, PCA can reveal whether this consistency reflects a single dominant factor or a more complex multidimensional structure. This provides a more nuanced understanding of whether each RESET component is cohesive and substantively meaningful. At the same time, PCA may also expose tensions between statistical groupings and

predefined theoretical constructs, as statistical coherence does not automatically coincide with conceptual alignment.

PCA also complements uncertainty and sensitivity analysis by offering a statistical perspective on the role and contribution of individual indicators within the overall structure of the index. It can highlight interdependencies among indicators, identify areas of redundancy and provide a useful benchmark for considering alternative weighting structures. In this respect, PCA may help explain why changes in certain methodological assumptions have limited or greater effects on results. However, because PCA-derived weights are based on statistical variance rather than policy relevance or expert judgement, they should be interpreted with caution and not seen as a substitute for theory-based choices. Moreover, PCA results are sensitive to preprocessing decisions, such as standardisation and normalisation, which means that its findings must be interpreted in conjunction with the broader methodological framework of the index.

PCA provides an additional layer of statistical validation by assessing whether the indicators within each component reflect the intrinsic structure of the data, while also helping to identify redundancy and refine the interpretation of internal coherence. At the same time, its limitations should be recognised: PCA can be technically demanding and less transparent to policymakers, and may produce results that do not fully align with the theoretical and policy-driven logic of the index. For this reason, PCA should be viewed as a complementary tool that strengthens, rather than replaces, the conceptual and methodological foundations of RESET (see Table 7).

Table 7. **Advantages and disadvantages of PCA compared with already used methods in the context of RESET**

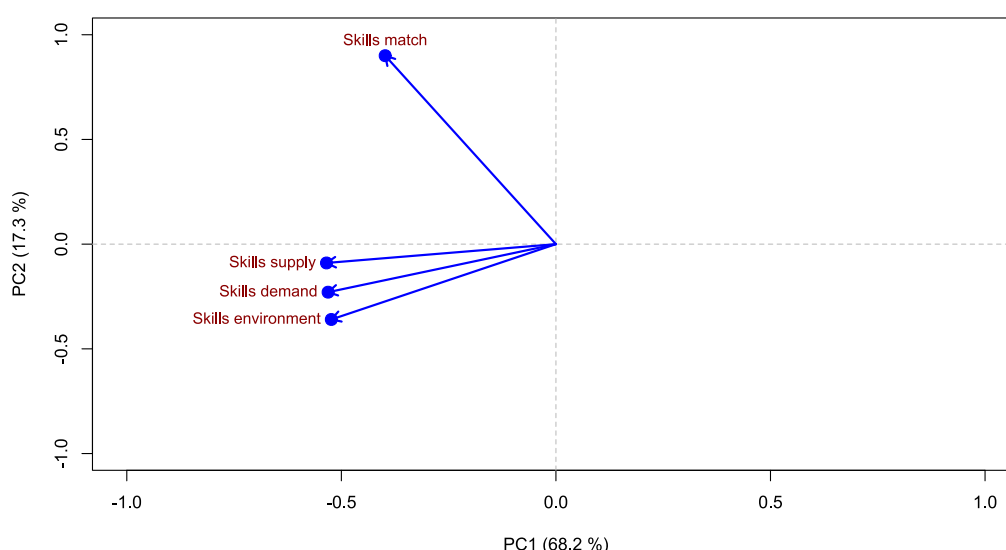
Aspect	Advantages of PCA	Disadvantages of PCA
Correlation analysis	Identifies latent structures in the data, complementing correlation analysis by highlighting clusters of indicators contributing to the same underlying dimension.	May oversimplify relationships by focusing only on variance, potentially overlooking theoretical alignments or subtle correlations identified through standard correlation analysis.
	Reduces redundancy among highly correlated indicators, offering a statistical basis for indicator selection or adjustment.	Requires a subjective interpretation of components, which may not align perfectly with the theoretical framework.
Reliability analysis	Validates findings from Cronbach's alpha by assessing whether consistency stems from a single dominant factor or multiple components, thus adding nuance to the reliability assessment.	PCA-derived groupings may not align with predefined theoretical constructs, creating potential conflicts with the conceptual framework.
	Enhances reliability by ensuring that pillars represent cohesive yet multidimensional constructs.	Can be computationally intensive and require specialised expertise for interpretation.
Uncertainty analysis	Provides an objective, data-driven method for generating weights, which can be compared against weights derived from expert judgement or sensitivity tests such as weight perturbation.	PCA-derived weights focus solely on variance, potentially ignoring policy- or stakeholder-driven priorities that are better captured through expert-defined weights.
	Highlights interdependencies among indicators, aiding in the evaluation of robustness under uncertain assumptions.	May require additional assumptions or transformations (e.g. standardisation) to produce interpretable components, which could introduce biases.
Sensitivity analysis	Identifies clusters of redundant indicators, complementing sensitivity analysis by suggesting where methodological adjustments (e.g. weighting) might have the greatest impact.	PCA's emphasis on statistical coherence may divert focus from the practical implications of methodological choices explored through sensitivity analysis.
	Facilitates exploration of methodological robustness by comparing outcomes of PCA-based weights with those derived through weight perturbation.	Results are highly dependent on the preprocessing of data (e.g. normalisation).
General reflections	Ensures that the index reflects the data's intrinsic structure, offering an additional validation layer to complement existing methods.	Risk of over-fitting the data, especially with small datasets or those with many missing values.
	Helps identify the most statistically significant indicators, enabling refinements to the theoretical framework and improving the overall coherence of the index.	Outputs can be less transparent and harder to communicate to policymakers than simpler, theoretically grounded methods like correlation or sensitivity analysis.

Source: Cedefop.

The sensitivity analysis revealed that aggregation is the primary driver of variability in RESET. This finding takes on additional significance when combined with PCA results: if indicator groupings demonstrate high internal coherence through PCA, this both validates the conceptual framework and suggests that variations in results stem primarily from legitimate methodological choices rather than from poorly aligned indicator groupings.

The PCA results at the index level reveal strong statistical coherence among the four pillars of RESET. To formally validate the statistical coherence of indicator groupings, we apply the Kaiser criterion, which stipulates that principal components with eigenvalues greater than 1 should be retained, as the primary diagnostic. An eigenvalue exceeding 1 indicates that the component captures more variance than any single standardised indicator would contribute individually, confirming that indicators share a meaningful common dimension (Kaiser, 1960).

Figure 20. **PCA factor map – four RESET pillars**



Source: Cedefop.

The factor map (see Figure 20) visualises the relationships between the four pillars in the space defined by the first two principal components. The arrows representing each pillar all point in similar directions, confirming their strong common variance captured by PC1. The separation visible along the vertical second principal component (PC2) axis illustrates the secondary dimension that differentiates skills match from skills environment, while skills demand and skills supply occupy intermediate positions. Although the PCA factor map shows a relatively close relationship between skills demand and skills environment (and also skills demand and skills supply), this proximity should not be interpreted as

sufficient evidence for merging the two pillars. The observed closeness reflects the fact that demand-side labour market conditions and the broader institutional, innovation and business environment are structurally interconnected in regional skills ecosystems. However, they remain conceptually and policy-relevant distinct domains: skills demand captures the nature and intensity of labour market needs, whereas skill environment reflects the enabling conditions that shape how skills are developed, absorbed and utilised. Therefore, the PCA result is best interpreted as evidence of expected interdependence rather than problematic redundancy. Retaining both pillars preserves the theoretical structure of the RESET framework and allows the index to distinguish between related but different mechanisms of regional skills performance.

Table 8 presents the complete PCA results across all aggregation groups, including eigenvalues, the share of variance explained and weight ranges. All 10 groups, that is, the four RESET pillars at the index level and nine sub-pillars at the component level, satisfy the Kaiser criterion, with PC1 eigenvalues ranging from 1.44 to 4.03. This universal compliance confirms that every indicator grouping in RESET captures a statistically meaningful latent construct rather than arbitrary noise.

A methodological note is warranted regarding the interpretation of PCA results. Several components in RESET contain deliberately paired indicators that measure the same underlying construct for different sub-populations (i.e. all graduates and IVET or secondary graduates only). These paired indicators carry a weight of 0.5 each in the index, reflecting the fact that together they represent a single conceptual dimension. However, PCA treats each indicator as a separate variable and does not account for the index weighting. As a result, components composed entirely of such pairs, notably ‘employment tasks’ (four indicators forming two pairs) and ‘activity and transition’ (six indicators forming three pairs), will show mechanically inflated PC1 variance because the built-in correlation between paired indicators boosts the common factor. Components with a mix of paired and unpaired indicators, such as ‘labour market imbalances’ and ‘skills formation’, are also affected but to a lesser extent. The components without any paired indicators, namely ‘employment and productivity’, ‘labour attraction’, ‘quality of business environment’, ‘education–business cooperation’ and ‘quality of education environment’, provide the most informative test of statistical coherence, as their PC1 results reflect genuine common variance among conceptually distinct indicators.

Table 8. **PCA results summary across all RESET aggregation groups**

Pillar	Component	Indicators	PC1 eigenvalue	Variance explained (%)	Weight range	Passes Kaiser criterion
—	Four pillars (index)	4	2.727	68.2	0.2-0.27	✓
Skills supply	Labour attraction	2	1.441	72	0.5 (equal)	✓
Skills supply	Skills formation	6	3.3	55	0.1-0.21	✓
Skills demand	Employment and productivity	6	4.034	67.2	0.14-0.19	✓
Skills demand	Employment tasks	4	3.352	83.8	0.24-0.26	✓
Skills match	Activity and transition	6	3.98	66.3	0.15-0.18	✓
Skills match	Labour market imbalances	6	3.822	63.7	0.13-0.19	✓
Skills environment	Quality of business environment	2	1.627	81.3	0.5 (equal)	✓
Skills environment	Quality of education environment	3	1.877	62.6	0.29-0.37	✓
Skills environment	Education–business cooperation	2	1.779	88.9	0.5 (equal)	✓

NB: Kaiser criterion requires eigenvalue > 1 for component retention. The weight range shows the spread of indicator loadings on PC1.

Source: Cedefop.

PC1 explains 68.2 % of the total variance, indicating that the pillars capture a unified underlying construct: the regional skills ecosystem. This high percentage suggests that regions performing well on one pillar tend to perform well on others, confirming the conceptual alignment of the framework. All four pillars load strongly and uniformly on PC1, with PCA-derived weights ranging from 0.20 to 0.27. This near-equality validates the current equal-weighting approach used in aggregation, confirming that all four pillars contribute comparably to the common dimension.

The skills supply pillar has two components: ‘labour attraction’ and ‘skills formation’. The ‘labour attraction’ component has no paired indicators and shows good coherence, with PC1 explaining 72.0 % of variance between its two indicators, and equal PCA weights (0.50 each), indicating that these labour attractiveness measures are well correlated and form a unified dimension. The ‘skills formation’ component comprises six indicators, of which one pair (adults with a learning experience, measured for all and for secondary education) carries 0.5 weights each. PC1 explains 55.0 % of variance, the lowest among all components,

with PCA weights ranging from 0.10 to 0.21. The relatively low coherence and wide weight range suggest that the six indicators capture somewhat diverse aspects of skills formation. This finding may warrant further review in future editions to determine whether the current grouping optimally reflects the construct, or whether a refined indicator selection could improve internal coherence. In the first edition of RESET, all indicators are kept securing a similar number of indicators across all pillars.

The skills demand pillar consists of 'employment and productivity' and 'employment tasks'. The 'employment tasks' component shows PC1 explaining 83.8 % of variance among its four indicators, with very balanced PCA weights (0.24 to 0.26). However, as noted above, all four indicators form two pairs, so this high coherence is largely a mechanical consequence of the pairing structure rather than evidence of convergence among distinct constructs. The 'employment and productivity' component provides a more informative test, as all six of its indicators are conceptually distinct and none of them form pairs. PC1 explains 67.2 % of variance with weights ranging from 0.14 to 0.19, demonstrating genuine statistical coherence among diverse productivity-related measures.

The skills match pillar encompasses the 'activity and transition' and 'labour market imbalances' components. The 'activity and transition' component shows PC1 explaining 66.3 % of variance among its six indicators, with well-balanced PCA weights (0.15 to 0.18). All six indicators in this component form three pairs, so the PC1 variance is partly inflated by the built-in correlation within pairs. The 'labour market imbalances' component shows PC1 explaining 63.7 % of variance among its six indicators, with PCA weights ranging from 0.13 to 0.19. This component contains a mix of paired indicators and unpaired indicators, so its coherence reflects both the pairing structure and genuine common variance among the distinct labour market imbalance measures.

The skills environment pillar has three components: 'quality of business environment', 'education–business cooperation' and 'quality of education environment'. None of these components contain paired indicators, so their PCA results provide an unambiguous test of statistical coherence. All three demonstrate internal coherence and they form unified dimensions. The 'education–business cooperation' component achieves the highest PC1 variance in the entire index at 88.9 %, with equal PCA weights (0.50 each). For the 'quality of business environment' component, 81.3 % of the variance is explained by PC1 between its two indicators, again with equal weights (0.50 each). The 'quality of education environment' component demonstrates just 62.6 % variance explained by PC1 among its three indicators. The PCA weights range from 0.29 to 0.37, confirming

that overall these dimensions form a relatively coherent construct for measuring the education environment.

The PCA results confirm the strong statistical coherence in the RESET framework. Seven out of ten components show PC1 variance above 65 %, and four exceed 70 %, indicating that most indicator groupings successfully capture common underlying dimensions. The index-level analysis, showing 68.2 % common variance among the four pillars, further validates the overall conceptual framework.

The near-equality of PCA-derived weights across most components supports the methodological choice to use equal weights in aggregation. This finding is particularly important considering the sensitivity analysis results, which showed that weight perturbation had a secondary impact on index variability. The PCA analysis provides a statistical rationale for this finding: when indicators within components are highly coherent and contribute roughly equally to the common dimension, variations in their weights naturally have limited effects on outcomes. This convergence between sensitivity analysis and PCA results strengthens confidence in the equal-weighting approach.

These findings complement the uncertainty and sensitivity analysis results presented in the previous section. The PCA analysis provides an orthogonal perspective on structural coherence. The strong PC1 values across most components suggest that the index structure itself is sound, even as the sensitivity analysis highlights that the choice between arithmetic and geometric mean aggregation fundamentally changes how compensability operates across indicators.

The PCA findings confirm that the index structure captures meaningful underlying dimensions, and that the dominant sensitivity to the aggregation method reflects a legitimate methodological choice rather than structural weaknesses in indicator groupings.

3.9. Data sense-making

Data cannot be properly interpreted without considering their contexts. To make sense of data, it is essential to ask: ‘Compared with what?’ This comparison allows for a clearer understanding of the information at hand. For the development of RESET, discussions within Cedefop throughout the entire development process have provided valuable insights into how contextual interpretation can influence the design and robustness of the index.

The context for data interpretation does not always come from the datasets themselves; it can also be derived from external sources such as literature reviews

or expert consultations. RESET's development process has reflected this, including a presentation to the European Association of Regional and Local Authorities for Lifelong Learning in April 2025 and the participation in the JRC COIN open days in October 2025. These consultations aimed to ensure that the index captures the complexity and nuances of the data and is aligned with the broader contextual framework. Engaging with this broader context enables the detection of possible errors and inconsistencies in the data, ensuring a more accurate and comprehensive analysis.

By situating data within their appropriate contexts and using visual tools to highlight relationships and patterns, we can enhance our ability to draw meaningful conclusions and make informed decisions. One outcome of these consultations is the results of a forthcoming accompanying Cedefop publication. It will present first analytical findings, including the association between RESET scores and key economic outcomes, an analysis of IVET graduate performance relative to the overall workforce, the identification of VET good-practice regions and a cluster analysis distinguishing four regional typologies with differentiated policy needs.

3.10. Visualisation

The final step in composite indicator development is presenting it in a clear and accessible format. This can include tables, charts and graphical representations that effectively communicate the results to the target audience. Proper documentation and transparency in the methodology are essential for ensuring the credibility and usability of the composite indicator. Effective presentation and dissemination contribute to the composite indicator's impact and enable stakeholders to understand its implications and make informed and results-based decisions. Effective presentation is crucial for ensuring that the composite indicator achieves its intended objectives and is widely accepted and used.

A RESET test platform was initially created to design a detailed and user-friendly interface for analysing and exploring regional skills ecosystems and to test it. The platform combined clear visuals, intuitive navigation and advanced data visualisation tools to present complex data in an accessible and meaningful way. Using dynamic maps, radar charts, scatterplots and bar charts, Cedefop test users gained valuable insights into regional performance, strengths and challenges across the various dimensions of regional skills ecosystems.

Overall, the RESET test platform provided a powerful environment to test-drive the presentation of RESET regional data. By presenting data in an intuitive and visually compelling way, the test platform was a first step towards a RESET web tool. The lessons learned from the RESET test platform have been taken on

board in the web tool and contribute to the effective presentation of RESET in support of evidence-based decision-making and regional development strategies.

Chapter 4.

Conclusion

This research paper has documented the construction and statistical validation of RESET, Europe's first composite indicator designed to measure and compare regional skills ecosystems across 244 NUTS 2 regions. The index is structured around four pillars (skills supply, skills demand, skills environment and skills match) and combines 37 indicators drawn from various sources. The research paper has detailed each stage of the index's development: the conceptual framework underpinning the selection and grouping of indicators, the data treatment and imputation procedures used to address missing values, the normalisation and aggregation methods applied, and the weighting strategy adopted.

RESET rests on a sound methodological foundation, both conceptually and statistically. Correlation analysis demonstrates strong internal coherence. The uncertainty analysis shows that most regional rankings remain stable within acceptable bounds. The Sobol' sensitivity decomposition identifies the aggregation method as the dominant source of ranking variance, with normalisation and weights each contributing modestly and imputation having negligible impact. The PCA results and the sensitivity findings converge: when indicators within components are highly coherent and contribute roughly equally to the common dimension, perturbations in their weights naturally have limited effects on outcomes, which is precisely what the sensitivity analysis confirms.

Together, the results presented in this paper show that RESET provides a reliable and robust basis for cross-regional comparison of skills ecosystem performance, and that its rankings reflect genuine differences in how regions develop, deploy and match skills within a given environment. The timeliness of this work is underscored by the communication on the Union of Skills (European Commission, 2025a), which considers skills to be key to strengthening competitiveness. It is also highlighted by the Council recommendation on human capital in the EU (Council of the European Union, 2026), which underlines the need to further integrate skills intelligence into the design of national, regional and local strategies and acknowledges the important territorial dimension of skills and human capital across Europe. RESET is well positioned to contribute to these objectives.

RESET is not only designed as a research output but intended to be a living tool that evolves through engagement with its target audiences. To that end, the index will be presented at flagship European events after its launch in 2026 and

beyond. Opportunities to gather feedback from practitioners and policymakers will be leveraged to understand how the index can best serve their needs and to identify priority areas for further development.

Several new analytical directions are envisaged for the future. A first line of work could examine temporal dynamics: as the underlying data are updated, tracking how regional scores evolve over time would allow for the identification of regions on improving or deteriorating trajectories, and help shed light on whether convergence or divergence is occurring across European regions. A second avenue could leverage the relationship between RESET and socioeconomic outcomes by investigating additional dimensions and by exploring whether the associations identified are mediated by specific pillars or indicator combinations. A third direction could examine the interplay between RESET pillars more closely. This could, for example, involve assessing whether improvements in the skills environment pillar are a precondition for progress in skills matching, or whether supply-side investments yield diminishing returns in the absence of corresponding demand. The VET-specific analysis initiated in the forthcoming accompanying RESET publication could be expanded by investigating which institutional and policy features distinguish regions where IVET graduates outperform the general population. Member-State-level deep dives could combine RESET data with information characterising the national policy context to produce case studies that illustrate how specific policy interventions relate to observed regional performance patterns.

A particularly promising direction concerns the identification and transfer of good and bad practices for regional skills ecosystems. RESET's comparative framework creates a natural basis for this work. Regions that achieve strong outcomes despite structural disadvantages are especially informative. For example, regions in lower-income Member States that nonetheless score well on specific pillars, or regions that have improved markedly over time, offer more transferable policy lessons than those of regions whose performance reflects long-standing resource advantages.

Case study research can pair the quantitative identification of positive outliers with qualitative field research. Interviews with regional stakeholders, analysis of local policy documents and mapping of institutional arrangements could provide valuable insight into what works and under what conditions. Comparative case studies of regions with similar economic structures but divergent RESET outcomes could attempt to isolate the policy and institutional factors that potentially drive differences. Peer learning exercises, in which higher- and lower-performing regions are matched based on their RESET profiles and supported in exchanging

practices, could be used to mainstream effective regional policy and its implementation.

The RESET tool's website already provides interactive features enabling users to explore regional profiles, compare regions and identify specific areas of relative strength or weakness. Over time, additional functionalities could be developed to enhance the platform, and pilot projects with selected regions could test how RESET evidence can be integrated into regional skills strategies, smart specialisation strategies or regional skills pacts. At the EU level, RESET supports the monitoring of policy frameworks such as the Skills observatory of the Union of Skills and the Council recommendation on human capital in the EU by providing a structured, regularly updated evidence base on the territorial dimension that the recommendation identifies as central.

The ideas outlined above represent current thinking on how RESET could develop further. Not all these directions can be pursued, and it will be important to assess the feasibility, resource requirements and expected impact of each before committing to a course of action. Prioritisation will be guided by stakeholder feedback, the availability of resources and suitable data, and the evolving policy context at the EU and national levels.

Abbreviations

COIN	Competence Centre on Composite Indicators and Scoreboards
COVID-19	Coronavirus disease 2019
CV	coefficient of variation
EQI	European Quality of Government Index
ETER	European Tertiary Education Register
EU	European Union
FUA	functional urban area
ISCED	International Standard Classification of Education
IVET	initial vocational education and training
JRC	Joint Research Centre
<i>k</i> -NN	<i>k</i> -nearest neighbours
LFS	Labour Force Survey
LMA	labour market area
LOCF	last observation carried forward
NACE	statistical classification of economic activities within the EU
NEETs	young people not in education, employment or training
NUTS	nomenclature of territorial units for statistics
OECD	Organisation for Economic Co-operation and Development
PC1	first principal component
PC2	second principal component
PCA	principal component analysis
RESET	Regional Skills Ecosystems index
sec	secondary education graduates
Si	first-order Sobol' index
Skills-OVATE	skills online vacancy analysis tool for Europe
STi	total-order Sobol' index
VET	vocational education and training

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Annexes

Annex 1.

Alternative regional classifications

Two alternative regional classifications have also been considered, each offering unique perspectives on defining and analysing regional skills ecosystems. These classifications are labour market areas (LMAs) and functional urban areas (FUAs), both of which have distinct advantages and limitations.

LMAs offer a functional perspective by defining regions based on commuting patterns and workforce interactions. Unlike NUTS, LMAs are not bound by administrative boundaries but are shaped by economic integration. Defined by self-containment and worker thresholds, LMAs can highlight economic integration and labour market dynamics within a region. LMAs offer several compelling advantages for analysing regional skills ecosystems. They align closely with real-world socioeconomic interactions, providing a granular perspective on local labour markets. This makes them particularly relevant for understanding the dynamics of workforce supply and demand at a localised level. Additionally, LMAs are inherently flexible, with parameters such as self-containment thresholds that can be adjusted to meet specific policy needs or research objectives. This adaptability ensures that they can be tailored to various contexts while maintaining analytical rigour. From a policy perspective, LMAs are especially valuable for evaluating the alignment of education and skills with labour market demands. By capturing the geographical context of commuting flows and local employment hubs, LMAs provide critical insights into how well regional education and training systems are meeting the needs of their respective economies. However, challenges include limited data availability for constructing LMAs at the EU scale and complexities in maintaining comparability across Member States.

FUAs represent another functional classification, focusing on urban agglomerations and their surrounding commuter zones. Like LMAs, FUAs are based on functional criteria, emphasising economic and social linkages rather than administrative boundaries. They are particularly useful for studying urbanisation, infrastructure needs and regional disparities. The advantages of FUAs include their relevance for urban-centred analyses and their ability to capture urban–rural linkages. However, their focus on urban dynamics may overlook rural labour markets and VET-specific challenges, limiting their applicability to the broader scope of skills ecosystems (see also Table 9).

Table 9. **Comparison of regional classifications**

Classification	Advantages	Limitations
NUTS 2	Extensive data availability; standardisation; alignment with EU indices.	Based on administrative boundaries; may not reflect functional economic regions.
LMAs	Real-world relevance; focus on labour market integration; flexible definition.	Data limitations; complexity in construction; limited cross-country comparability.
FUAs	Captures urban dynamics and urban–rural linkages; relevant for infrastructure.	Urban focus may overlook rural labour markets; limited focus on VET and skills ecosystems.

Source: Cedefop.

While LMAs and FUAs offer functional perspectives that align closely with the concept of skills ecosystems, the choice of NUTS 2 for RESET was primarily driven by practical considerations. NUTS 2 provides the most comprehensive and comparable dataset at the EU level, ensuring robust statistical analyses and integration with existing indices. Moreover, the standardisation of NUTS 2 allows RESET to build on established frameworks, enabling insights into regional skills dynamics while maintaining coherence with broader EU policy tools.

Annex 2.

Alternative advanced imputation methods

Alternative advanced statistical methods present potential avenues for further refinement of the imputation strategy, though they come with important practical considerations. Expectation maximisation algorithms, which use iterative maximum likelihood estimation to impute missing values while accounting for correlations among all variables simultaneously, could potentially capture complex multivariate relationships in regional skills ecosystem data. However, expectation maximisation approaches face computational challenges when applied to high-dimensional datasets, particularly when the number of variables approaches or exceeds the number of observations. This unfavourable ratio of parameters to observations can lead to estimation instability and convergence difficulties, potentially requiring either dimension reduction through indicator selection or application to specific subsets of the index.

Multiple imputation approaches, which generate several plausible values for each missing observation to reflect imputation uncertainty, could provide additional robustness checks and confidence intervals for regional rankings. These methods offer the appealing advantage of quantifying imputation uncertainty, allowing policymakers to understand the degree of confidence associated with regional rankings. However, multiple imputation via chained equations and similar approaches can encounter numerical instability in high-dimensional settings where variables exhibit strong multicollinearity, a common feature in composite indicators where related indicators naturally co-vary. The computational intensity of generating multiple imputed datasets and the potential for near-singular covariance matrices in contexts with many correlated indicators represent practical constraints on the application of these methods to the full RESET framework.

Table 10 summarises the advantages and disadvantages of the current imputation methods used in RESET and the proposed alternative methods.

Table 10. **Advantages and disadvantages of alternative imputation methods**

Method	Advantages	Disadvantages
Current methods		
Temporal imputation	• Leverages historical trends for stable indicators. • Effective for slow-moving variables like education levels.	• Assumes stability or gradual change, which may not hold for dynamic variables.
Spatial imputation using regional median	• Maintains regional patterns by leveraging higher-level aggregates (e.g. NUTS 1 data). • Simple to implement. • Robust against outliers. • Provides a central tendency estimate for sparse data.	• Can oversimplify differences between regions. • Relies on assumptions about geographical similarity. • Ignores variability among regions. • May lack precision for diverse datasets.
Spatial imputation using regional mean	• Maintains regional patterns by drawing on higher-level regional aggregates. • Simple and transparent to implement. • Uses all available values in the reference group. • Can provide a representative estimate when regional variation is limited.	• Sensitive to outliers and extreme values. • Can mask heterogeneity across regions. • Relies on assumptions about geographical similarity. • May be less robust than the median for skewed distributions.
k-NN	• Non-parametric, no distributional assumptions. • Captures non-linear relationships. • Adaptive to local patterns.	• Computationally intensive for large datasets. • Sensitive to choice of <i>k</i> and distance metrics. • Ineffective with sparse data.
Multiple imputation methods		
Expectation maximisation	• Statistically rigorous, maximising likelihood. • Suitable for strong multivariate correlations.	• Assumes normal distribution, which may not fit all indicators. • Sensitive to outliers. • May converge to suboptimal solutions.
Multiple imputation	• Accounts for uncertainty in missing data. • Flexible for different data types and distributions. • Enhances reliability of statistical inferences.	• Computationally expensive. • Complex to implement and interpret. • Requires careful tuning to balance fit and variability.

Source: Cedefop.

Each of these methods has distinct advantages and limitations, making them suitable for different contexts. However, following discussion with JRC COIN experts during the COIN open day in October 2025, it has been decided that these alternative methods are not necessary given the robustness of the methods that have already been implemented.

Annex 3.

Extended treatment pass methodology

In case indicators remain problematic after the first two steps, a second treatment stage repeats winsorisation with up to seven values. In principle, this winsorisation could even be tested before applying the logarithmic transformation, but in the case of RESET indicators it would not change the results compared to winsorisation with five values. If outliers persist, a Box-Cox or similar transformation can be conducted. If this is not enough, a third treatment stage employs advanced transformation techniques designed to fundamentally reshape distributions. This stage categorises remaining problematic indicators by severity and applies transformations accordingly. Depending on the level of kurtosis, a rank-based transformation, a quantile normalisation, an inverse hyperbolic sine transformation or a second round of aggressive winsorisation is attempted.

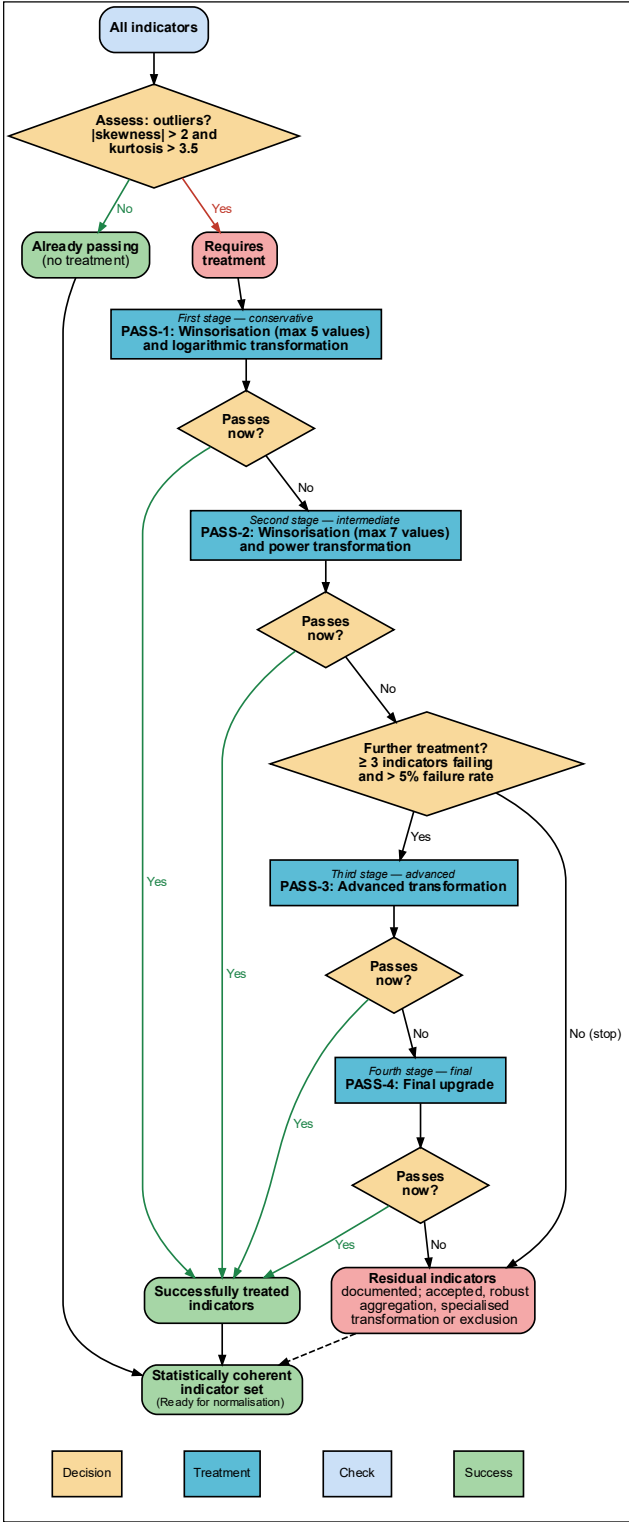
A fourth and final treatment pass is available for indicators that remain problematic despite three prior interventions. This stage applies upgraded versions of third-stage transformations, recognising that indicators reaching this stage are likely to have fundamental distributional characteristics that resist conventional treatment. For instance, quantile normalisation may be applied to indicators that previously received inverse hyperbolic sine transformation or aggressive winsorisation in the third stage, escalating to the most powerful distribution-reshaping technique available.

However, indicators requiring third- or fourth-stage treatment are rare in practice, and their need for such intensive transformation may signal underlying data quality issues or structural characteristics that merit substantive investigation beyond statistical treatment.

A critical feature of this treatment methodology is its implementation of intelligent stopping criteria that prevent over-treatment and computational waste. For example, third and fourth treatment passes could be initiated if (1) at least three indicators remain problematic and (2) the failure rate exceeds 5 % of the total indicator set.

When these stopping criteria are met, the methodology terminates, and then generates comprehensive documentation of which indicators remain problematic, by what margin they exceed thresholds and what treatments were attempted. This transparency enables informed decision-making about how to handle residual cases, whether through acceptance as near-threshold exceptions, application of specialised techniques or consideration for exclusion from the composite indicator.

Figure 21. Multi-pass statistical treatment methodology



Source: Cedefop.

Figure 21 presents a complete overview of the multi-pass treatment methodology, illustrating the sequential nature of the four treatment passes, the intelligent stopping criteria that determine whether to proceed beyond the second pass and the convergence of all successfully treated indicators into a statistically coherent set ready for normalisation. The flow chart emphasises the key principle that each indicator receives only one treatment, namely the first pass that successfully brings it within acceptable thresholds, thereby avoiding over-treatment while ensuring comprehensive coverage of all problematic cases.

Annex 4.

Indicator details

Table 11. Overview on indicator details

(Sub)pillar	Variable name	D	W	Age (years)	Years	Source	Nominator	Denominator	Note
Skills supply – skills formation	NEET	–1	1	15–29	2019–2024	Eurostat (edat_lfse_22)	Young persons neither in employment nor in education and training	Total population	X
Skills supply – skills formation	Basic digital technology knowledge	–1	1	16–74	2018–2024	Eurostat (isoc_r_iuse_i)	Individuals who used the internet; internet use: never	Total population	NUTS 1 in Germany and Greece
Skills supply – skills formation	Adults with a learning experience (all)	1	0.5	25–64	2022–2024	Eurostat – LFS extraction (for Cedefop)	Persons who received education or training (last 12 months), all International Standard Classification of Education (ISCED) levels	Total population	X
Skills supply – skills formation	Adults with a learning experience (secondary)	1	0.5	25–64	2022–2024	Eurostat – LFS extraction (for Cedefop)	Persons who received education or training (last 12 months), ISCED 3–4	Total population	X
Skills supply – skills formation	Student population	1	1	n/a	2018–2024	Eurostat (educ_uoe_enra11, demo_r_d2jan)	Pupils and students enrolled in pre-primary to tertiary education	Total population, 25–64 years	NUTS 1 in Germany
Skills supply – skills formation	Higher education graduates	1	1	25–64	2019–2024	Eurostat (edat_lfse_04)	Population in private households with ISCED 5–8 as the highest level of education successfully completed	Total population	X

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(Sub)pillar	Variable name	D	W	Age (years)	Years	Source	Nominator	Denominator	Note
Skills supply – labour attraction	Net migration	1	1	n/a	2022–2024	Eurostat (demo_r_gind3)	Net migration plus statistical adjustment	1 000 of the average population	5-year rolling averages
Skills supply – labour attraction	Attraction of foreign higher education graduates	1	1	n/a	Sum (2018–2022)	ETER project data; download date: 22 October 2025	Graduates at ISCED 5–7 – foreigner	Graduates at ISCED 5–7 – national	Sum is taken to increase the number of regions with available data
Skills demand – employment and productivity	Labour productivity	1	1	25–64	2018–2024	Eurostat (nama_10r_2nlp)	Nominal labour productivity	Hours worked	Indexed to EU average (100)
Skills demand – employment and productivity	Compensation of employees	1	1	25–64	2018–2024	Eurostat (nama_10r_2coe, demo_r_d2jan)	Compensation of employees in million euro	Total population, 25–64 years	X
Skills demand – employment and productivity	Green pervasiveness	1	1	n/a	2020–2024	Cedefop Skills-OVATE data	Number of online job advertisements containing at least one green skill	Total number of online job advertisements	X
Skills demand – employment tasks	Cognitive tasks (IVET)	–1	0.5	15–74	2022	Eurostat ad hoc module 2022 extraction (for Cedefop)	Employed persons by working time spent on cognitive tasks: little or none, ISCED 35–45	Employed persons by working time spent on cognitive tasks: total, ISCED 35–45	
Skills demand – employment tasks	Cognitive tasks (all)	–1	0.5	15–74	2022	Eurostat ad hoc module 2022 extraction (for Cedefop)	Employed persons by working time spent on cognitive tasks: little or none, all ISCED levels	Employed persons by working time spent on cognitive tasks: total, all ISCED levels	
Skills demand – employment tasks	Digital tasks (IVET)	–1	0.5	15–74	2022	Eurostat ad hoc module 2022 extraction (for Cedefop)	Employed persons by working time spent on using digital devices: little or none, ISCED 35–45	Employed persons by working time spent on using digital devices: total, ISCED 35–45 graduates	

Annex 4.
Indicator details

(Sub)pillar	Variable name	D	W	Age (years)	Years	Source	Nominator	Denominator	Note
Skills demand – employment tasks	Digital tasks (all)	–1	0.5	15–74	2022	Eurostat ad hoc module 2022 extraction (for Cedefop)	Employed persons by working time spent on using digital devices: little or none, all ISCED levels	Employed persons by working time spent on using digital devices: total, all ISCED levels	
Skills demand – employment and productivity	Highly skilled employed people	1	1	25–64	2022–2024	Eurostat – LFS extraction (online available)	Highly skilled employed people	Total number of people employed	X
Skills demand – employment and productivity	Scientists and engineers	1	1	15–74	2018–2024	Eurostat (hrst_st_rcat)	Scientists and engineers	Population in the labour force	X
Skills demand – employment and productivity	Employment in hi-tech sectors	1	1	15–74	2018–2024	Eurostat (htec_emp_reg2)	Employed persons in hi-tech sectors (hi-tech manufacturing and knowledge-intensive hi-tech services)	Total employment	X
Skills match – activity and transition	Employment of young graduates (IVET)	1	0.5	20–34	2019–2024	Eurostat (edat_ifse_33)	Employed young persons not in education and training, duration since completion of highest level of education: total, ISCED 35–45	Total population, duration since completion of highest level of education: total, ISCED 35–45	X
Skills match – activity and transition	Employment of young graduates (all)	1	0.5	20–34	2019–2024	Eurostat (edat_ifse_33)	Employed young persons not in education and training, duration since completion of highest level of education: total, all ISCED levels	Total population, duration since completion of highest level of education: total, all ISCED levels	X
Skills match – labour market imbalances	Unemployment (IVET)	–1	0.5	15–74	2019–2024	Eurostat – LFS extraction (for Cedefop)	Unemployed persons, ISCED 35–45	Total population in the labour force, ISCED 35–45	X

(Sub)pillar	Variable name	D	W	Age (years)	Years	Source	Nominator	Denominator	Note
Skills match – labour market imbalances	Unemployment (all)	–1	0.5	15–74	2019–2024	Eurostat (lfst_r_lfu3rt)	Unemployed persons, all ISCED levels	Total population in the labour force	X
Skills match – labour market imbalances	Labour market slack	–1	1	15–74	2019–2024	Eurostat (lfst_r_sla_ga)	Persons with labour force and employment status: labour market slack	Extended labour force	X
Skills match – labour market imbalances	Macroeconomic skills mismatch	–1	1	25–64	2019–2024	Eurostat (lfst_r_lfe2eedu, lfst_r_lfsd2pop)	Employed persons and total population for specific ISCED group	Employed persons and total population for all ISCED levels	Specific formula: Vandeplas and Thum-Thysen (2019), p. 7
Skills match – labour market imbalances	Long-term unemployment (all)	–1	0.5	15–74	2018–2024	Eurostat (lfst_r_lfu2ltu)	Persons in long-term unemployment (12 months or more), all ISCED levels	Total population in the labour force, all ISCED levels	X
Skills match – labour market imbalances	Long-term unemployment (secondary)	–1	0.5	15–74	2018–2024	Eurostat (lfst_r_lfu2ltu)	Persons in long-term unemployment (12 months or more), ISCED 35–45	Total population in the labour force, ISCED 35–45	X
Skills match – activity and transition	Activity of adult persons (all)	1	0.5	25–64	2018–2024	Eurostat (lfst_r_lfp2actrt)	Active persons, all ISCED levels	Total population	X
Skills match – activity and transition	Activity of adult persons (IVET)	1	0.5	25–64	2019–2024	Eurostat – LFS extraction (for Cedefop)	Active persons, ISCED 35–45	Total population	X
Skills match – activity and transition	Activity of young persons (all)	1	0.5	15–24	2019–2024	Eurostat (lfst_r_lfp2actrt)	Active persons, all ISCED levels	Total population	X
Skills match – activity and transition	Activity of young persons (IVET)	1	0.5	15–24	2019–2024	Eurostat – LFS extraction (for Cedefop)	Active persons, ISCED 35–45	Total population	X

(Sub)pillar	Variable name	D	W	Age (years)	Years	Source	Nominator	Denominator	Note
Skills environment – education–business cooperation	Higher education–business cooperation (EU projects)	1	1	n/a	Sum (2018–2022)	ETER project data (download date: 22 October 2025); Eurostat (demo_r_d2jan)	Number of EU framework programmes for research and technological development participations with at least one company partner	Total population (millions) in 2021	Sum is taken to increase the number of regions with available data
Skills environment – education–business cooperation	Higher education co-publications with industry	1	1	n/a	Sum (2018–2022)	ETER project data (download date: 22 October 2025); Eurostat (demo_r_d2jan)	Co-publications with industrial partners	Total population (millions) in 2021	Sum is taken to increase the number of regions with available data
Skills environment – quality of education environment	Quality of public education	1	1	18+	2021, 2024	EQI 2021, 2024	Average rating: quality of public education in the area	n/a	X
Skills environment – quality of education environment	Equal treatment in education	–1	1	18+	2021, 2024	EQI 2021, 2024	Average rating: all citizens are treated equally in the public education system in the area	n/a	X
Skills environment – quality of education environment	Integrity issues in public education	–1	1	18+	2021, 2024	EQI 2021, 2024	Average rating: corruption is prevalent in the area's local public school system	n/a	X
Skills environment – quality of business environment	Business sophistication	1	1	25–64	2018–2024	Eurostat (lfst_r_lfe2en2)	Employed persons, statistical classification of economic activities within the EU (NACE), sections K–N	Employed persons, all NACE sections	Definition from European Commission, 2023b, p. 34

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(Sub)pillar	Variable name	D	W	Age (years)	Years	Source	Nominator	Denominator	Note
Skills environment – quality of business environment	Working from home	1	1	20–64	2019–2024	Eurostat – LFS extraction (for Cedefop)	Home working: usually	Home working: total (including no working at home)	X

NB: D = direction (i.e. the data are inverted in case of a negative (–1) direction); n/a = not applicable; W = weight.

Annex 5.

Regions included

Table 12. Overview of regions included (plus Member States and EU average)

NUTS code	Type	NUTS code	Type	NUTS code	Type	NUTS code	Type
EU27_2020	EU average	DED2	Region	FRM0	Region	AT12	Region
BE	Member State	DED4	Region	FRY1	Region	AT13	Region
BE10	Region	DED5	Region	FRY2	Region	AT21	Region
BE21	Region	DEE0	Region	FRY3	Region	AT22	Region
BE22	Region	DEF0	Region	FRY4	Region	AT31	Region
BE23	Region	DEG0	Region	FRY5	Region	AT32	Region
BE24	Region	EE	Member State	HR	Member State	AT33	Region
BE25	Region	EE00	Region	HR02	Region	AT34	Region
BE31	Region	IE	Member State	HR03	Region	PL	Member State
BE32	Region	IE04	Region	HR05	Region	PL21	Region
BE33	Region	IE05	Region	HR06	Region	PL22	Region
BE34	Region	IE06	Region	IT	Member State	PL41	Region
BE35	Region	EL	Member State	ITC1	Region	PL42	Region
BG	Member State	EL30	Region	ITC2	Region	PL43	Region
BG31	Region	EL41	Region	ITC3	Region	PL51	Region
BG32	Region	EL42	Region	ITC4	Region	PL52	Region
BG33	Region	EL43	Region	ITF1	Region	PL61	Region
BG34	Region	EL51	Region	ITF2	Region	PL62	Region
BG41	Region	EL52	Region	ITF3	Region	PL63	Region
BG42	Region	EL53	Region	ITF4	Region	PL71	Region
CZ	Member State	EL54	Region	ITF5	Region	PL72	Region
CZ01	Region	EL61	Region	ITF6	Region	PL81	Region
CZ02	Region	EL62	Region	ITG1	Region	PL82	Region
CZ03	Region	EL63	Region	ITG2	Region	PL84	Region
CZ04	Region	EL64	Region	ITH1	Region	PL91	Region
CZ05	Region	EL65	Region	ITH2	Region	PL92	Region
CZ06	Region	ES	Member State	ITH3	Region	PT	Member State
CZ07	Region	ES11	Region	ITH4	Region	PT11	Region
CZ08	Region	ES12	Region	ITH5	Region	PT15	Region
DK	Member State	ES13	Region	ITI1	Region	PT19	Region
DK01	Region	ES21	Region	ITI2	Region	PT1A	Region

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NUTS code	Type	NUTS code	Type	NUTS code	Type	NUTS code	Type
DK02	Region	ES22	Region	ITI3	Region	PT1B	Region
DK03	Region	ES23	Region	ITI4	Region	PT1C	Region
DK04	Region	ES24	Region	CY	Member State	PT1D	Region
DK05	Region	ES30	Region	CY00	Region	PT20	Region
DE	Member State	ES41	Region	LV	Member State	PT30	Region
DE11	Region	ES42	Region	LV00	Region	RO	Member State
DE12	Region	ES43	Region	LT	Member State	RO11	Region
DE13	Region	ES51	Region	LT01	Region	RO12	Region
DE14	Region	ES52	Region	LT02	Region	RO21	Region
DE21	Region	ES53	Region	LU	Member State	RO22	Region
DE22	Region	ES61	Region	LU00	Region	RO31	Region
DE23	Region	ES62	Region	HU	Member State	RO32	Region
DE24	Region	ES63	Region	HU11	Region	RO41	Region
DE25	Region	ES64	Region	HU12	Region	RO42	Region
DE26	Region	ES70	Region	HU21	Region	SI	Member State
DE27	Region	FR	Member State	HU22	Region	SI03	Region
DE30	Region	FR10	Region	HU23	Region	SI04	Region
DE40	Region	FRB0	Region	HU31	Region	SK	Member State
DE50	Region	FRC1	Region	HU32	Region	SK01	Region
DE60	Region	FRC2	Region	HU33	Region	SK02	Region
DE71	Region	FRD1	Region	MT	Member State	SK03	Region
DE72	Region	FRD2	Region	MT00	Region	SK04	Region
DE73	Region	FRE1	Region	NL	Member State	FI	Member State
DE80	Region	FRE2	Region	NL11	Region	FI19	Region
DE91	Region	FRF1	Region	NL12	Region	FI1B	Region
DE92	Region	FRF2	Region	NL13	Region	FI1C	Region
DE93	Region	FRF3	Region	NL21	Region	FI1D	Region
DE94	Region	FRG0	Region	NL22	Region	FI20	Region
DEA1	Region	FRH0	Region	NL23	Region	SE	Member State
DEA2	Region	FRI1	Region	NL32	Region	SE11	Region
DEA3	Region	FRI2	Region	NL34	Region	SE12	Region
DEA4	Region	FRI3	Region	NL35	Region	SE21	Region
DEA5	Region	FRJ1	Region	NL36	Region	SE22	Region
DEB1	Region	FRJ2	Region	NL41	Region	SE23	Region
DEB2	Region	FRK1	Region	NL42	Region	SE31	Region
DEB3	Region	FRK2	Region	AT	Member State	SE32	Region
DEC0	Region	FRL0	Region	AT11	Region	SE33	Region

Regional Skills Ecosystems index (RESET)

Leveraging Europe's competitiveness with cutting-edge regional skills intelligence

The Regional Skills Ecosystems index (RESET) is a significant step forward in the development of intelligence for regional skills ecosystems in the European Union. RESET introduces a much-needed regional lens to skills and vocational education and training (VET), highlighting their pivotal role in fostering inclusive and sustainable growth. This regional skills intelligence offers policymakers a unique opportunity to design more effective skills strategies. Covering 244 regions, it captures the interplay between education and training, between education and business, and between workers and learners – and highlights the role of VET not only in promoting efficient education-to-work transitions but also in sustaining employability and advancing lifelong learning.

This research paper presents the conceptual and methodological development of RESET, including data collection, imputation, outlier treatment, normalisation, weighting and aggregation. Statistical coherence, robustness and sensitivity analyses are also performed. The results show that RESET offers a reliable and robust basis for comparing skills ecosystem performance across regions.



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