Labor Data Readiness in the Age of AI: Building the Foundations for Smarter Workforce Planning

workday.

Access Partnership

January 2026

Table of Contents

Executive summary

Artificial intelligence (AI) is reshaping labor markets at a speed and scale that existing labor market information systems are not equipped to track. Most countries rely on infrequent surveys, broad occupational categories, and siloed administrative datasets—producing backward-looking indicators that say who works where, but very little about what they actually do, what skills they use, or how AI is changing tasks and driving increased opportunities for employers, job seekers, and incumbent workers. Without more granular, agile, and interoperable labor market data, policymakers risk missing early signals of disruption, mistargeting training investments, and slowing workforce adjustment in the AI-driven world.

The objective of this paper is to help governments modernize their labor market data systems in order for them to be better able to navigate an AI-driven economy. It establishes a global baseline, assesses system gaps, and presents a structured pathway to strengthen a country's readiness to cope with labor market changes due to AI adoption.

A maturity framework has been developed to benchmark the AI readiness of 21 countries across six dimensions: Forecasting Readiness, Labor Market Granularity, Accessibility, Interoperability and Integration, and Real-time Responsiveness (FLAIR).

It is crucial to recognize that this assessment reflects an emergent economic landscape for which many national labor market systems were not originally architected. Consequently, this analysis should not be interpreted as an identification of systemic deficiencies, but as a strategic identification of opportunities to evolve. The countries assessed have established strong foundations, and our findings are intended to highlight practical pathways to build on these strengths and align existing infrastructures with the rapidly changing demands of labor market reporting in an AI-driven economy.

Main insights:

1. Across the 21 countries assessed, every country achieves frontier or near-frontier performance (level 3 or 4) in at least one FLAIR dimension, reflecting strong foundations on which labor data modernization could be further accelerated.
2. Nearly all countries (20 out of 21 countries) have aligned their national labor systems or maintained crosswalks with international standards such as the International Standard Classification of Occupations (ISCO), indicating a strong foundation for interoperability.
3. Most countries (71%) produce medium- to long-term labor projections, but these remain conventional and occupation-based. No country has yet adopted AI-enabled or task-level scenario modelling, which is essential for anticipating AI-driven disruptions.
4. More than half of the countries (57%) publish monthly labor force data that can be leveraged to develop near real-time forecasting and monitoring.

5. There is a gap in capturing data at the task or skill level through core national surveys; currently, only a few countries supplement their official statistics with external task-level datasets.
6. While only a minority of countries (four out of 21 countries) currently offer open, machine-readable, application programming interface (API) enabled labor datasets at the micro level, the underlying technology is already mature and operational in other statistical domains across many countries, demonstrating a trend to move away from static reports or restricted microdata and toward more dynamic and scalable access models.
7. Public–private data partnerships are emerging, but integration remains limited. In most cases, private data—such as online job postings—feeds into dashboards or pilots rather than being incorporated into official labor statistics.

While several countries operate at level 3 or above in multiple dimensions under the FLAIR framework, none consistently attains the most advanced level across all areas, highlighting potential opportunities to strengthen the granularity and integration of the labor market data system.

Main recommendations:

1. **Data Collection.** Modernize labor force surveys and administrative datasets to capture tasks, skills, digital tools, and AI use. Adopt longitudinal, forward-looking designs and leverage selected AI-enabled tools to improve data quality and reduce collection burdens.
2. **System Foundations.** Build the technical architecture that allows labor data to function as a coherent, interoperable system rather than a collection of isolated datasets. This includes co-developing and adopting shared task- and skill-level taxonomies, ensuring interoperability with global standards, and transitioning to machine-readable, API-enabled data platforms.
3. **Intelligence Capabilities.** Shift from descriptive reporting to anticipatory intelligence by strengthening forecasting models, integrating high-frequency private sector data, and improving the timeliness of indicators through automated nowcasting pipelines.
4. **Governance and Partnerships.** Establish clear mandates, support voluntary public-private partnerships, and multi-stakeholder governance. Position governments as the institutional backbone that anchors labor market data reform by setting standards and mandates, with industry supporting real-time labor signals and methodological insights through voluntary public-private partnerships.

Modern labor market data is no longer a technical upgrade but a strategic necessity. Countries that fail to modernize risk flying blind: missing early signals of AI-driven change, mistargeting training investments, and weakening their competitiveness and workforce resilience in an AI-shaped global economy. Those that advance across the six dimensions of the FLAIR Framework will be better positioned to anticipate disruption, guide reskilling, and align skills systems with industrial and innovation strategies.

1. Introduction

1.1. AI and the rapidly evolving landscape of occupations and skills

AI has moved from specialized applications to widespread use across industries, reshaping how work is organized and performed.[1] Rather than eliminating entire occupations, AI primarily transforms tasks within jobs, automating routine and codifiable activities while complementing complex cognitive and interpersonal tasks.[2] As a result, even workers in the same occupation can face very different forms of exposure depending on their task mix and skill proficiency.

This shift is not only changing existing jobs but also creating entirely new ones. Roles such as AI trainers, AI ethicists, explainability experts, and prompt engineers, which did not exist a few years ago, are now emerging rapidly.[3] At the same time, online job posting data reveals constant re-bundling and evolution of digital and AI-related skills, illustrating how demand for capabilities is shifting across occupations and regions in real time.[4] Recent studies suggest that roughly a quarter of job roles worldwide will be disrupted by 2027, with 69 million new jobs expected to be created and 83 million displaced—a net shift that underscores the scale and speed of labor market transformation.[5]

However, current labor data systems are struggling to keep pace with these developments. Core elements of the institutional architecture, occupational classifications, are typically updated on multi-year or even decade-long cycles, even as skill requirements evolve on a quarterly or annual basis.[6, 7, 8, 9] This structural mismatch creates an inherent lag between how work is evolving and how it is measured and managed in official statistics. Further, new AI-driven roles like "large language model engineer" or "blockchain developer" are absent or not well-defined in current taxonomies.[10] This misalignment poses challenges for measuring employment trends and skills gaps in emerging fields.

Consequently, policymakers increasingly require visibility into task-level and skill-level dynamics, as research shows that most technology-induced labor market adjustments occur within occupations rather than between them.[11] High-frequency signals, from digital platforms, human resource (HR) systems, and online labor markets, have become critical for anticipating disruptions and identifying emerging skills. [12]

---

1 OECD (2023), "OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market." Available at: https://www.oecd.org/employment/oecd-employment-outlook-19991266.htm

2 Melanie Arntz, Terry Gregory, and Ulrich Zierahn (2016) "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis." *OECD Social, Employment and Migration Working Papers*. Available at: https://wecglobal.org/uploads/2019/07/2016_OECD_Risk-Automation-Jobs.pdf

3 Timothy Prestianni (2025), "59 AI Job Statistics: Future of U.S. Jobs". *National University.* Available at: https://www.nu.edu/blog/ai-job-statistics/

4 Mariagrazia Squicciarini and Heike Nachtigall (2021), "Demand for AI skills in jobs: Evidence from online job postings", *OECD Science, Technology and Industry Working Papers.* Available at: https://www.oecd.org/en/publications/demand-for-ai-skills-in-jobs_3ed32d94-en.html

5 World Economic Forum (2023), "Future of Jobs Report 2023". Available at: https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf

6 International Labour Organization (ILO) (2022), "Revision of the International Standard Classification of Occupations (ISCO-08)". Available at: https://unstats.un.org/unsd/classifications/Meetings/UNCEISC2022/UNCEISC_2022_meeting_Session_7b3_ISCO-08_Revision.pdf

7 ILO, "International Standard Classification of Occupations (ISCO)". Available at: https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/

8 ILO (2020), "The feasibility of using big data in anticipating and matching skills needs". Available at: https://www.ilo.org/sites/default/files/wcmsp5/groups/public/%40ed_emp/%40emp_ent/documents/publication/wcms_759330.pdf

9 OECD (2024), "Artificial intelligence and the changing demand for skills in the labour market". Available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/artificial-intelligence-and-the-changing-demand-for-skills-in-the-labour-market_861a23ea/88684e36-en.pdf

10 Monica Sanders (2024), "Unlocking The Future Of Work by Updating Federal Job Classifications", *Federation of American Scientists.* Available at: https://fas.org/publication/future-of-work-classifications/

11 Brynjolfsson, Mitchell & Rock (2018), "What Can Machines Learn and What Does It Mean for Occupations and the Economy?" Available at: https://www.aeaweb.org/articles?id=10.1257/pandp.20181019

12 OECD (2022), "Skills for Jobs 2022". Available at: https://www.oecdskillsforjobsdatabase.org/data/S4J2022_results.pdf

1.2. The need for modern, agile, and precise labor market data in the AI-driven world

As AI accelerates changes in the world of work, modern, agile, and precise labor market data is becoming a critical public good. Traditional labor market information systems built around infrequent surveys, broad occupational categories, and siloed administrative datasets are no longer adequate for understanding or managing the speed and complexity of AI-driven change. Policymakers, job seekers, and incumbent workers now require labor market intelligence that is granular, frequent, and interoperable, enabling comparison across data systems and countries through shared classifications and crosswalks.

Such capabilities transform labor data from a static reporting function into a strategic tool for economic management and potentially drive key opportunities for employers, job seekers, and incumbent workers. Granular, high-frequency data enables governments and institutions to anticipate disruptions early, detect emerging opportunities, and design timely interventions that support workers, employers, and regional economies. Without these systems, countries risk missing early signals of displacement or growth and remaining ill-equipped to manage AI-driven workforce transitions.

Importantly, the benefits of modern labor market data extend across the entire ecosystem:

- Job seekers and incumbent workers would gain clearer visibility into emerging roles, required skills, and career pathways, supporting informed transitions in a rapidly evolving labor market.
- Employers would benefit from accurate, real-time signals on skill shortages, emerging demand, and shifting task profiles, enabling more effective recruitment, workforce planning, and investment in reskilling.
- Training institutions would be able to deliver cost-effective reskilling programs aligned with industry needs, enabling job seekers and incumbent workers to upskill efficiently in line with evolving skills demands.
- Governments would rely on precise labor market intelligence to anticipate disruptions, target interventions, guide industrial and skills strategies, and allocate training resources to areas of future need.

The broader labor market system becomes more efficient overall, with fewer skill mismatches, lower structural unemployment, and stronger alignment between workforce capabilities and economic transformation.

In short, agile, skills-aware labor market data is no longer a technical enhancement. It is an essential foundation for inclusive, resilient governance in the AI era, and for informed policy development to support job seekers and incumbent workers.

1.3. Objectives and scope of this report

This report examines how national governments and multilateral organizations (MLOs) can accelerate the development of modern, AI-ready labor market data systems to strengthen workforce resilience, economic adaptability and agility, drive skills transformation, and support long-term economic resilience. The study aims to establish a global baseline of labor data system readiness, identify key gaps, highlight best practices, and develop a practical maturity model that governments can use to benchmark and guide improvement. It also seeks to position labor data reform as a strategic enabler of AI-era workforce resilience and a foundation for advancing data-driven workforce transformation.

The report structure is as follows:

- **Chapter 2: Landscape review on labor data and future skills.** This chapter reviews current international and national approaches to labor data, assesses strengths and limitations, and highlights opportunities to adapt existing frameworks for AI-era workforce planning.
- **Chapter 3: Building the labor data maturity framework and country tier definitions.** This chapter introduces a practical maturity framework to benchmark country AI readiness, focusing on frequency, granularity, interoperability, and forecasting capacity. It also identifies best practices in capturing, analyzing, and using AI-relevant labor data in collaboration with MLOs to support national systems in tracking AI-related labor market change. Based on this framework, countries are classified into tiers of readiness, ranging from advanced systems with granular, real-time data to those with limited, aggregate-only data collection. This typology illustrates the spectrum of current capabilities and provides a reference point for targeted reforms and interventions.
- **Chapter 4: Policy recommendations.** This chapter provides actionable guidance for governments, MLOs, and industry partners. It outlines the design of a minimum viable labor data system, proposes short-, medium-, and long-term reform pathways, and highlights opportunities for international collaboration, diagnostic assessments, and regional peer learning platforms to strengthen implementation.

2. Landscape review on labor data

Labor data systems are a cornerstone of workforce planning, yet most are not designed to capture or respond to the rapid shifts introduced by AI and related technologies. Current approaches typically rely on labor force surveys (LFS), population censuses, and administrative records such as unemployment insurance claims or tax filings. While potentially rich in information, these datasets are often aggregated at broad occupational or sectoral levels, updated on annual or multi-year cycles, and rarely interoperable across education, training, and employment systems. As a result, policymakers struggle to anticipate fast-moving shifts in labor demand or identify emerging skills in real time. This hinders governments from effectively informing and funding timely, targeted interventions, which are necessary to ensure the current and future workforce has the skills demanded by upcoming technological developments. It also limits the agility that job seekers and incumbent workers urgently require.

While skills taxonomies and databases provide valuable descriptions of competencies, they face a core limitation: labor data systems themselves are not designed to capture, integrate, and respond to AI-enabled labor markets. A review of international and national labor data systems shows that they remain rooted in occupation- or industry-level reporting, lack sufficient detail, are revised too slowly to capture emerging dynamics, and diverge in their organizing principles, undermining cross-country comparability. Against this backdrop, five limitations are significant.

Lack of granularity in labor data that captures the skills of workers

A central limitation of contemporary labor market information (LMI) systems is that they measure jobs rather than skills. Core statistical pipelines—most notably LFS and administrative reporting—are organized around occupational and industrial classifications such as the ISCO, International Standard Industrial Classification of All Economic Activities (ISIC), and North American Industry Classification System (NAICS).[13] These frameworks enable consistent reporting of employment, unemployment, wages, and hours by occupation and industry; however, they do not directly observe the skills or tasks performed within jobs. As a result, the statistical record provides robust counts of who works where, but limited evidence on what capabilities are used or how work content changes as technologies diffuse. The U.S. Bureau of Labor Statistics (BLS) has acknowledged this gap, noting that occupational data alone is an inadequate proxy for skills, especially for cognitive capability, unless supplemented with external task- or skill-based sources.[14]

Beyond occupational codes, education levels are also often used as proxies for skills in LMI systems, but these, too, fall short. For example, the International Labour Organization's (ILO) guidelines on measuring qualification and skill mismatches emphasize that educational attainment alone is insufficient and that LFS instruments must include skill-related job characteristics to capture mismatches and meaningfully identify policy levers.[15]

---

[13] Sources include: International Labour Organization (n.d.), "International Standard Classification of Occupations (ISCO)". Available at: https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/; United Nations Statistics Division (2008), "International Standard Industrial Classification of All Economic Activities (ICIS), Rev.4". Available at: https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf; and United States Census Bureau (n.d.), "North American Industry Classification System". Available at: https://www.census.gov/naics/

[14] BLS (2020), "Assessing the Impact of New Technologies on the Labor Market: Key Constructs, Gaps, and Data Collection Strategies for the Bureau of Labor Statistics". Available at: https://www.bls.gov/bls/congressional-reports/assessing-the-impact-of-new-technologies-on-the-labor-market.pdf

[15] International Labour Organization (2018), "Measurement of qualifications and skills mismatches of persons in employment". Available at: https://www.ilo.org/media/211731/download

Dedicated skills frameworks exist, but they remain disconnected from core labor statistics. For example, the European Skills, Competences, Qualifications and Occupations (ESCO) in Europe and the Occupational Information Network (O*NET) in the U.S. provide rich descriptors of skills, knowledge, and tasks. Yet, national labor indicators rarely link microdata directly to these taxonomies.[16] For example, the Organisation for Economic Co-operation and Development's (OECD) Skills for Jobs database attempts to infer shortages by combining multiple data sources. Still, it cautions about measurement and representativeness issues, highlighting the persistent separation between skills evidence and headline labor data.[17]

The absence of task or skill-level granularity, especially measures with intensity or proficiency scales, limits policy relevance. Studies show that AI tends to substitute routine tasks and complement non-routine tasks, with much of the adjustment occurring within occupations rather than through wholesale occupational shifts.[18] Without such task-level mapping and worker-level proficiency indicators, policymakers risk misclassifying exposure, mistargeting training, and slowing adjustment to AI.

Recent innovations point to progress, but they remain add-ons rather than integrated solutions. The BLS has introduced "skills by occupation" tables, derived from O*NET, and developed cognitive and mental requirement profiles through the Occupational Requirements Survey (ORS). However, these remain linked to occupational categories rather than being collected as standalone variables in the LFS. The methodological advance is in linkage, not yet in fully integrated skill capture within national LMI systems. Consequently, policymakers still lack a routinely updated, skill-native evidence base capable of distinguishing how work is changing within occupations, which tasks are expanding or contracting, and where targeted training or technology adoption would have the greatest impact.[19, 20]

Refresh cycles are too slow for AI-era policy making

Most occupational classification systems are refreshed on multi-year cycles that are fundamentally out of step with the speed of technological change. The ILO ISCO was published in 2008, and the next revision is only expected around the 2030 census round.[21] While the ILO has acknowledged the need for more detailed skill-level measurement, the long revision timeline risks falling behind recent labor market dynamics.[22] Additionally, the ESCO framework is updated every two to five years, with the most recent release in May 2024.[23] This cadence is too sluggish to capture

16 Sources include: European Commission (n.d.), "European Skills, Competences, Qualifications and Occupations (ESCO)". Available at: https://esco.ec.europa.eu/en/classification; and O*Net (n.d.), "See All Occupations". Available at: https://www.onetonline.org/find/all

17 Sources include: OECD (2022), "OECD Skills for Jobs". Available at: https://www.oecdskillsforjobsdatabase.org/press.php; OECD (2022), "Skills for Jobs 2022". Available at: https://www.oecdskillsforjobsdatabase.org/data/S4J2022_methods.pdf

18 Makela, E., and Stephany, F. (2025), "Complement or substitute? How AI increases the demand for human skills". Available at: https://arxiv.org/pdf/2412.19754

19 U.S. Bureau of Labor Statistics (2024), "A new data product for occupational skills: methodology, analysis, and a guide to using the employment projections skills data". Available at: https://www.bls.gov/opub/mlr/2024/article/a-new-data-product-for-occupational-skills.htm

20 U.S. Bureau of Labor Statistics, "Occupational Requirements Survey: Concepts". Available at: https://www.bls.gov/opub/hom/ors/concepts.htm

21 ILO, "The revision of ISCO-08". Available at: https://isco-ilo.netlify.app/en/news/

22 International Conference of Labor Statisticians (2023), "Overview of the progress of work in revising ISCO-08 and major recent developments". Available at: https://unstats.un.org/unsd/classifications/Meetings/UNCEISC2023/Session12_Pres3_ISCO-08_Revision_bis.pdf

23 European Skills, Competences, Qualifications and Occupations (ESCO). Available at: https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/esco-versions

newly emerging occupations and skills, such as AI-related roles, leaving them unrecognized or folded into broad, outdated categories.[24]

National systems face similar challenges. The Korean Standard Classification of Occupations (KSCO), for example, was updated in 2024—seven years after the previous revision in 2017, which itself followed a ten-year gap since 2007.[25] Such lags demonstrate the structural inability of many classification systems to remain policy relevant in fast-changing labor markets.

Evidence from international organizations reinforces the importance of more agile updates. OECD work highlights that automated web scraping of online job postings enables the rapid collection of comprehensive labor market data, providing timely insights into sector and occupational trends as well as skill and work experience requirements.[26] While traditional survey- and register-based methods remain essential for producing consistent, nationally representative labor market indicators. Their methodological rigor provides the foundation on which all other analysis rests. But they are often fielded only quarterly or annually and released with publication lags of several months, making it harder for policymakers to track rapid shifts in skills demand in real time.[27] The OECD's recent labor productivity nowcasting work further underscores the value of integrating high-frequency data streams to generate more timely and reliable estimates than official statistics alone can typically provide.[28] Together, this evidence highlights the need to complement static classifications with dynamic signals such as job postings, Human Resources Information System (HRIS) feeds, and administrative data—providing policymakers with the near real-time visibility required to anticipate and address disruptions, not simply document them after they occur.

National systems are not aligned with global standards

Cross-country comparability is undermined by the fact that the world's major occupational classification systems are built on different organizing logics. The ISCO, maintained by the ILO, is structured around the competency levels required to perform an occupation. Many countries base their national classifications on this framework, including the UK's Standard Occupational Classification (SOC), the KSCO, the Australian and New Zealand Standard Classification of Occupations (ANZSCO), and the Singapore Standard Occupational Classification (SSOC). By contrast, the U.S. SOC, developed by the U.S. BLS, is organized around specific tasks and activities carried out by workers and serves as the backbone of both federal and state-level labor statistics. O*NET further extends U.S. SOC into a skills and work content database, but it remains rooted in this task-based principle.[29]

---

24 Statistics Netherlands (2025), "Dutch AI monitor 2024". Available at: https://www.cbs.nl/en-gb/longread/aanvullende-statistische-diensten/2025/ai-monitor-2024/6-demand-for-workers-with-ai-skills

25 Korean Standard Classification of Occupations. Available at: http://kssc.kostat.go.kr/ksscNew_web/ekssc/common/selectIntroduce.do?part=2&top_menu=101&bbsId=isco_s&categoryNameCode=801&categoryMenu=001

26 Wessel Vermeulen and Fernanda Gutierrez Amaros (2024), "How well do online job postings match national sources in European countries?", *OECD Local Economic and Employment Development.* Available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/03/how-well-do-online-job-postings-match-national-sources-in-european-countries_5e6fb2bd/e1026d81-en.pdf

27 Ibid.

28 OECD Statistics (2025), "Nowcasting labor productivity growth with machine learning and mixed-frequency data". Available at: https://oecdstatistics.blog/2025/03/31/nowcasting-labor-productivity-growth-with-machine-learning-and-mixed-frequency-data/

29 Ospino, Carlos (2018), "Occupations: Labor Market Classifications, Taxonomies, and Ontologies in the 21st Century", Inter-American Development Bank (IDB). Available at: https://publications.iadb.org/en/occupations-labor-market-classifications-taxonomies-and-ontologies-21st-century

This misalignment creates practical problems for workforce planning. While crosswalks exist to map ISCO and U.S. SOC to each other, the divergent principles underlying them—competency versus task orientation—make full harmonization difficult. The European Commission's effort to build a technical crosswalk between ESCO and O*NET underscores both the importance of comparability and the challenges involved; alignment requires extensive methodological work and still leaves room for misclassification.[30] Empirical evidence reinforces this challenge: for example, a 2019 study in Germany finds that inter-agency occupational coding reliability can be low and often varies systematically across coding authorities.[31] Without harmonized standards, governments risk drawing inconsistent policy conclusions, misallocating training resources, and failing to coordinate effectively on global labor market shocks and migration management.

Private sector frameworks further compound the fragmentation. Each taxonomy and framework relies on proprietary systems designed to optimize data from digital platforms rather than on statistical comparability.[32] While some providers maintain crosswalks to ISCO or U.S. SOC for research partnerships,[33] the coverage is uneven and often stronger for white-collar roles than for blue-collar or informal employment.[34] This uneven ecosystem makes it difficult to build a globally consistent evidence base for workforce planning, especially amid AI-driven occupational change.

Gaps in forecasting capabilities

Most national labor market information systems are primarily descriptive, offering backward-looking snapshots of employment, unemployment, and wages. They provide little predictive power for anticipating how technological change will reshape the demand for occupations and skills. Forecasting capacity remains underdeveloped, often limited to medium-term labor force projections or sectoral demand estimates,which do not capture the within occupation dynamics or skill substitution effects central to AI-driven transformation.

The OECD has noted that many countries lack the methodological infrastructure to translate skill taxonomies and historical demand into forward-looking models, leaving governments reliant on ad hoc surveys or qualitative foresight exercises.[35] At the same time, the OECD highlighted that public labor data platforms lag in updates, user friendliness, and real-time functionality, further limiting their usefulness for anticipating change.[36] This underscores the urgent need to build stronger forecasting systems that are explicitly tied to evolving skill requirements and labor market dynamics.[37] The shortfall is not only technical but also institutional: few statistical agencies maintain dedicated

---

30 ESCO Publications (2022), "The crosswalk between ESCO and O*NET (Technical Report)". Available at: https://esco.ec.europa.eu/en/about-esco/publications/publication/crosswalk-between-esco-and-onet-technical-report

31 Massing et al. (2019), "How Standardized is Occupational Coding? A Comparison of Results from Different Coding Agencies in Germany", *Journal of Official Statistics.* Available at: https://doi.org/10.2478/jos-2019-0008

32 Josh Bersin (2025), "People Data For Sale: How The Talent Intelligence Market Really Works". Available at: https://joshbersin.com/2025/07/people-data-for-sale-how-the-talent-intelligence-market-works/

33 Lightcast (2025), "Workforce Estimation Model (WEMo)". Available at: https://kb.lightcast.io/en/articles/8582979-workforce-estimation-model-wemo

34 Eoin D. (2024), "LinkedIn Downsides: Where are the blue-collar workers?". *LinkedIn.* Available at: https://www.linkedin.com/pulse/linkedin-downsides-where-blue-collar-workers-eoin-dolly-pqdff/

35 OECD (2023), "Assessing and Anticipating Skills for the Green Transition: Unlocking Talent for a Sustainable Future", Getting Skills Right, OECD Publishing, Paris. Available at: https://doi.org/10.1787/28fa0bb5-en

36 OECD (2025), Empowering the Workforce in the Context of a Skills-First Approach, OECD Skills Studies, *OECD Publishing, Paris*. Available at: https://doi.org/10.1787/345b6528-en

37 Ibid.

forecasting units capable of generating iterative scenarios to stress test training systems or reskilling strategies. As a result, labor market policy remains largely reactive, intervening only after dislocations become visible, rather than anticipatory and preventive.

Limited accessibility to data

A further limitation is that many labor data systems remain difficult to access or integrate across domains. While international platforms such as ILOSTAT or OECD Data provide open access to headline indicators, many national datasets are locked in aggregated PDFs or tables, with little machine-readability or real-time interoperability.[38] This restricts how data can be linked to education, training, or social protection systems, capabilities that are critical for designing coordinated workforce policies and ensuring countries can respond quickly to the disruptive pressures of AI-driven labor market changes.

The ILO's Labor Market Information Systems Toolkit highlights the necessity of data accessibility for stakeholders to seamlessly share and exchange labor market information.[39] Yet in practice, accessibility varies significantly: some countries, such as the U.S. BLS, provide APIs and user-friendly platforms that allow data retrieval and integration, while others rely primarily on static survey reports published in aggregate formats, offering limited granularity and little support for automated analysis.

In summary, no single dataset can capture the full spectrum of occupational changes in a fast changing labor market under AI. Future-ready labor systems need to merge multiple data sources to detect both macro trends and skill-level shifts. Potential sources include national occupation classification systems, surveys, administrative records, HRIS data, and private sector labor market data providers. Integration can help address a critical need to link people's actual tasks at work with official statistics. To make this integration effective, interoperable standards such as the Statistical Data and Metadata eXchange (SDMX) are critical for merging labor statistics with other socio-economic datasets in real time, improving their value for AI-era workforce planning.[40]

---

38 Based on Access Partnership's analysis of labor market data for this study. Details are listed in Appendix B.

39 ILO (2023), "LMIS: Brief Description and ILO Toolkit". Available at: https://www.ilo.org/sites/default/files/2024-05/LMIS%20-%20Brief%20description%20and%20ILO%20Toolkit%20%28Dec2023%29.pdf

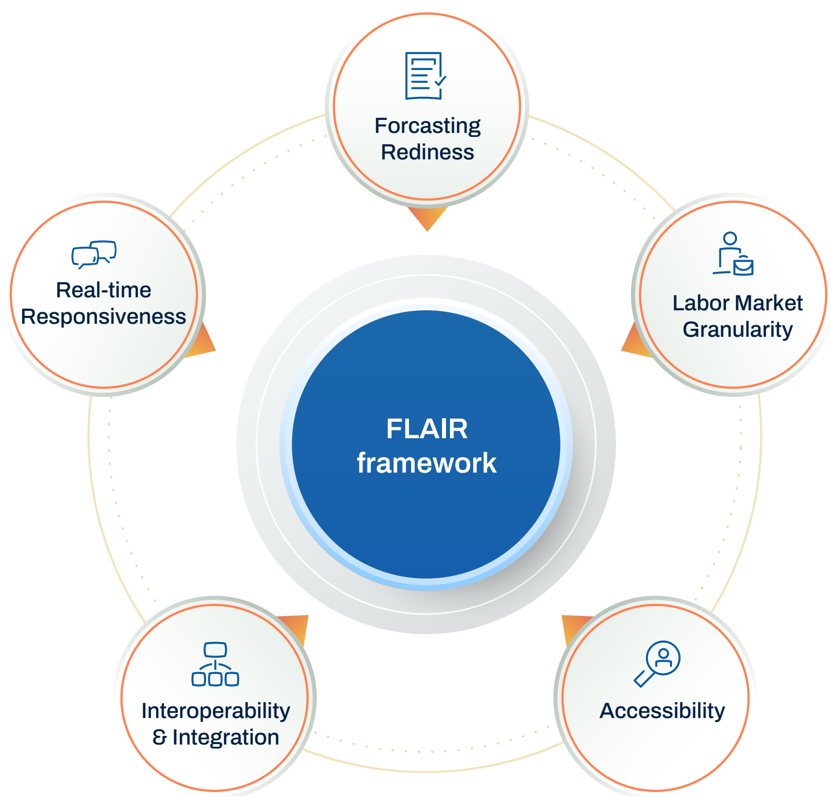
40 ILOSTAT (n.d), "SDMX tools". Available at: https://ilostat.ilo.org/resources/sdmx-tools/

3. Building the labor data maturity framework and country tier definitions

As AI accelerates change in the world of work, existing labor data frameworks reveal not only their limitations but also important opportunities for improvement. The need is no longer theoretical: policymakers, employers, job seekers, and incumbent workers require systems that can capture fast-changing realities, anticipate disruptions, and inform timely interventions. To move beyond fragmented efforts, there is a need for a systematic framework that benchmarks where countries stand today and identifies clear pathways for improvement. This study introduces a labor data maturity framework, designed to map key weaknesses in current systems to measurable elements of maturity, and to provide a structured basis for cross-country tiering. The framework builds on the issues of current labor market data identified in Chapter 2. This excludes elements that are important in an AI world but are already present in current labor market data, such as demographic disaggregation.

3.1. Labor Data Maturity Framework

Exhibit 1: Labor data maturity framework



The framework, also referred to as FLAIR, is structured around six essential dimensions—Forecasting Readiness, Labor Market Granularity, Accessibility, Interoperability and Integration, and Real-time Responsiveness (Exhibit 1), each of which reflects a core requirement for AI-ready labor data systems as highlighted in Chapter 2. Together, these elements provide a structured basis for benchmarking maturity across countries. When aligning with national strategies, FLAIR translates measurement to actions, informing investment and governance choices to strengthen skills development pipelines, enable industrial transformation, and advance inclusion.

Forecasting Readiness

Most labor statistics today remain descriptive, focused on reporting what has already happened rather than anticipating what is likely to come. In an AI-driven world, this backward-looking orientation leaves policymakers reacting only once disruptions are already visible. The next frontier is to move from descriptive analysis toward predictive and scenario-based modelling, which anticipates labor market shifts before they occur.

Modern forecasting capacity should leverage task- and skill-level taxonomies, historical demand trends, and scenario modelling to anticipate mismatches in labor supply and demand, wage effects, and retraining requirements. Establishing dedicated forecasting units capable of producing iterative projections can help governments generate rolling, evidence-based projections rather than ad hoc surveys or qualitative foresight exercises, which are insufficient in the face of AI-driven change.

This indicator assesses the existence and quality of labor market outlooks, forecasting reports, and related analytical outputs published by Departments or Ministries of Labor and other official national government sources.

Scale:

- 1 = Descriptive statistics only
- 2 = Short-term projections (1–2 years)
- 3 = Medium- to long-term projections (3 years or more)
- 4 = AI-enabled foresight tools, task-level scenario modelling

Labor Market Granularity

Capturing labor market complexity in an AI-driven world requires going beyond aggregate occupational categories to reflect the actual tasks and skills that workers perform. This is done at an economy-wide level with sufficient subnational details. There are two key dimensions of granularity (in combination with real time responsiveness that is treated separately below): the first is economy-wide coverage, which reflects the level of detail, including the ability to capture tasks, competencies, skills, and proficiency, within current jobs and merging roles across both formal and informal employment. The second is geographic coverage, which is the ability to observe these role- and skill-level patterns across at national, subnational, regional and local level.

No single dataset currently available can reflect these levels of detail. Future-ready systems will therefore need to integrate multiple high-frequency, economy-wide sources—national occupational classifications, LFS, administrative records, HRIS datasets, and voluntary public-private partnership arrangements—to detect both macro trends and skill-level shifts, including task content in informal and platform-mediated work and across regions and local labor markets.

Such integration addresses a critical gap: linking what workers actually do with what is recorded in official statistics. OECD's Skills for Jobs database illustrates that multi-source integration can enrich analysis, though current coverage remains uneven.[41] Embedding task- and skill-level information, ideally with proficiency or intensity scales (e.g., beginner, intermediate, advanced), ensures that workers both inside and outside formal payrolls (e.g., gig and informal workers) are represented in skill measures, and that these measures can be routinely disaggregated to subnational, regional, and, where feasible, local levels. This allows policymakers to distinguish between people within the same occupation who face very different risks or opportunities depending on their task mix and where they are located, and to identify where emerging roles and skill shortages are geographically concentrated.

This indicator measures the level of detail captured in national occupation classifications and national LFS, and the extent to which these systems incorporate or link to task- and skill-level data. Since most countries have nationally representative LFS that generally allow some subnational disaggregation, geographic coverage is not used as an explicit assessment criterion. In practice, however, sample sizes, implementation capacity, and confidentiality constraints often limit the ability to monitor emerging roles and skills at finer regional or local levels. Data is typically reliable only for a limited set of regions or metropolitan areas, with emerging occupations and niche skill clusters effectively invisible below that threshold. Designing survey samples, rotation patterns, and linkages to administrative and private data with geographic granularity in mind is therefore an essential design priority for AI-ready labor market data systems.

Scale:

- 1 = Aggregate occupational categories, with ISCO 1-2 digits or equivalent
- 2 = Occupation-level data, with ISCO 3-4 digits or equivalent
- 3 = Task-level or partial skill descriptions included
- 4 = Detailed task- and skill-level data with intensity/proficiency levels.

[41] OECD (2017), "Getting Skills Right: Skills for Jobs Indicators", *OECD Publishing, Paris*. Available at: http://dx.doi.org/10.1787/9789264277878-en

Accessibility

Labor data remains unevenly accessible across countries: while some national agencies provide APIs, machine-readable datasets, and user-friendly platforms that enable integration across policy, research, and training systems, others still rely on static PDF reports with limited granularity.

To be effective in the AI-driven world, the modernization of the labor systems requires a cloud-first, privacy-preserving infrastructure with open APIs, standardized formats, and secure data sharing. In practice, this means leveraging digital public infrastructure to make data easy to discover, retrieve, and integrate at scale, improving efficiency, inclusion, resilience, and innovation while lowering transaction costs and safeguarding trust. OECD study highlights digital public infrastructure's role in improving public and private sector resource allocation efficiency and enabling innovation.[42] Additionally, the World Economic Forum (WEF) underscores the need for accessibility, safety, and trustworthiness.[43]

This indicator is assessed based on the accessibility and data sharing features of the national LFS or other equivalent official government labor datasets, including their availability in open, machine-readable, and API access.

Scale:

- 1 = Restricted, no public access
- 2 = Public reports only
- 3 = Open microdata
- 4 = Fully open, machine-readable, API-enabled, with cross-system integration

Interoperability

Despite progress, labor data systems today remain fragmented. International and national classifications are often built on different organizing principles, which limit cross-country benchmarking. In today's labor market, where mobility is increasingly common and workers can relocate globally, ensuring comparability across countries is critical for both workforce planning, migration management, and talent attraction, enabling employers and policymakers to better recognize and value skills acquired abroad.

Developing shared backbones and open crosswalks would allow countries to align training systems, benchmark more effectively, and coordinate responses to global shocks. Systematic international cooperation on interoperability is therefore a prerequisite for building AI-ready labor market governance and for strengthening countries' ability to compete for global talent.

---

[42] OECD (2024), "Digital Public Infrastructure for Digital Governments", *OECD Publishing, Paris.* Available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/12/digital-public-infrastructure-for-digital-governments_11fe17d9/ff525dc8-en.pdf

[43] Dylan Reim and Judith Vega (2025), "Why digital public infrastructure is key to building a connected future", *World Economic Forum (WEF).* Available at: https://www.weforum.org/stories/2025/04/digital-public-infrastructure-building-connected-future/

This indicator is assessed based on the alignment of national occupation classifications and LFS with international standards such as ISCO and U.S. SOC, and the presence of open crosswalks or data frameworks enabling cross-country comparability.

Scale:

- 1 = No harmonization or crosswalks available
- 2 = Partial mapping to international standards
- 3 = Formal crosswalks exist, but are not systematically applied
- 4 = Full alignment with open, regularly updated crosswalks across major frameworks

Integration with Private Data

Voluntary public–private partnership agreements to integrate private data are increasingly vital for capturing the real-time evolution of skills and jobs. Digital labor platforms, professional networks, and analytics providers collect rich, near real-time information on skills demand, job postings, and workforce mobility, which can complement national statistics. When structured properly, such partnerships can strengthen national capacity for anticipatory policymaking, inform curriculum updates, and identify emerging occupations early.

This indicator is assessed based on the existence of national initiatives, working groups, data sharing protocols, or formal cooperation frameworks that engage private data providers or digital labor platforms, and the extent to which official labor statistics incorporate or draw upon private sector datasets for analysis or forecasting.

Scale:

- 1 = No private data usage
- 2 = Ad hoc research partnerships
- 3 =Structured data-sharing arrangements
- 4 = Fully integrated systems

Real-time Responsiveness

Traditional labor data systems, such as LFS and census, provide valuable benchmarks, but the slow updating cycles leave policymakers reacting too late to disruptions. In the AI era, where occupational demand can shift within weeks, this cadence is insufficient.

The opportunity lies in combining annual or multi-year baselines with weekly or monthly nowcasts derived from administrative records and digital sources such as job postings or HRIS feeds. OECD research on online vacancy data demonstrates the feasibility of this approach, where digital labor demand signals complement official surveys by providing near real-time visibility into dynamics.[44] Embedding such high-frequency inputs into national systems ensures that data moves from retrospective reporting to anticipatory guidance.

This indicator is assessed based on the update frequency of the national LFS or population census.

Scale:
- 1 = Updates more than every 5 years
- 2 = Annual updates
- 3 = Quarterly updates
- 4 = Monthly or more frequent updates (near real-time)

3.2. Applying the framework: Cross-country analysis

A comparative review across six dimensions—forecasting readiness, labor market granularity, accessibility, interoperability, integration with private data, and real-time responsiveness—shows solid foundations but uneven progress toward AI-era, task- and skill-aware labor governance. We apply the six dimensions across the 21 selected countries (Exhibit 2).[45] Standout practices exist, yet end-to-end systems that translate high-frequency signals into official indicators and program decisions remain rare.[46] Notably, every country demonstrates a clear strength with at least one indicator scoring 3 or 4, reflecting a baseline readiness to transition towards a future-ready labor market system. Although these strengths vary across countries, the overall pattern of results highlights the most consistent gaps, helping to pinpoint the highest priority areas for improvement.

It is crucial to outline that our assessment reflects a strong foundational level across all analyzed countries and is calibrated to a new and rapidly evolving reality, one for which many existing national labor data systems were not originally designed. The findings should therefore not be interpreted as identifying deficiencies or shortcomings, but rather as highlighting areas of potential growth and development. These opportunities are intended to support more dynamic, future-oriented labor market data reporting in a context where policy, technological, and labor market demands continue to evolve.

44 OECD (2021), "An assessment of the impact of COVID-19 on job and skills demand using online job vacancy data", OECD Policy Responses to Coronavirus (COVID-19), *OECD Publishing, Paris*. Available at: https://doi.org/10.1787/20fff09e-en

45 The 21 countries were selected to capture technically mature, data-rich labor market systems with broad geographic coverage across North America, Europe, the Middle East and Africa (EMEA), and Japan and Asia-Pacific (JAPAC). These are economies with relatively well-established statistical infrastructures, regular labor force reporting, and active engagement in digitalization and AI, allowing us to compare diverse institutional models while ensuring sufficient data quality and granularity for assessment.

46 The detailed methodology for the cross-country assessment is provided in Appendix A, and the reference documents and sources used to inform each assessment are provided in Appendix B.

Exhibit 2: Comparative assessment of labor market data readiness based on FLAIR framework

	Forecasting Readiness	Labor Market Granularity	Accessibility	Interoperability	Integration	Real-time Responsiveness
Average across countries*	◑	◑	◕	◕	◑	●
Australia	◕	◑	◑	◕	◕	●
Belgium	◕	◑	◕	●	◑	◕
Canada	◕	◔	◕	◕	◑	●
Denmark	◕	◑	◕	●	◑	●
Finland	◕	◑	●	●	◕	●
France	◕	◔	◕	◕	◕	◕
Germany	◕	◔	◕	◕	◑	●
Ireland	◔	◔	◕	◕	◑	◕
Italy	◕	◑	◕	●	◕	◕
Japan	◔	◔	◑	◔	◔	●
Kingdom of Saudi Arabia	◕	◔	◑	●	◑	◕
Netherlands	◕	◔	◕	●	◕	◕
Norway	◕	◑	◑	●	◕	●
Singapore	◑	◔	◕	◕	◕	●
South Africa	◔	◑	◕	●	◑	◕
South Korea	◔	◑	◑	●	◕	●
Spain	◕	◔	●	◕	◑	◕
Sweden	◕	◑	◑	●	◕	●
United Arab Emirates	◔	◔	◑	●	◕	◑
United Kingdom	◕	◑	●	◕	◕	●
United States	◕	◑	●	◕	◔	●

Note: *The average score across the 21 countries for each indicator is rounded down to the nearest whole number.

Forecasting Readiness. Across the analysis, 71% of countries sit at level 3, producing medium- to long-term projections (Exhibit 2), though most outputs are still static, report style publications. The U.S., Canada, and Australia maintain structured occupational and industry projection datasets with horizons up to 2035; forming a strong backbone for workforce planning even though these remain conventional projections rather than AI-enabled.[47, 48] Germany's "Sixth Wave of Qualifications and Occupation Projections (from 2020)" extends to 2040 and is accompanied by a public dashboard, illustrating strong transparency and user access.[49] Through the European Centre for the Development of Vocational Training (CEDEFOP), European Union (EU) countries are covered by skills forecast studies, which project the labor market outlook through 2035, giving the members a shared evidence base for labor-market coordination.[50] France complements these system-wide projections with targeted occupation outlooks that inform national priority setting.[51] The UK similarly conducted skill priority assessments looking to 2030.[52] The Kingdom of Saudi Arabia (KSA) publishes annual employment outlook reports, with the most recent edition projecting occupation changes through 2034.[53] By contrast, Singapore's forecasting remains short horizon: its earlier study analyzed historical data from 2022 to 2024 and projected demand for priority skills to 2025.[54]

Looking ahead, the United Arab Emirates (UAE) Ministry of Human Resources & Emiratisation (MoHRE) has publicly positioned itself as a digital-innovation benchmark and signaled AI-enabled forecasting services on its roadmap.[55] While not yet live, this direction exemplifies the next step for all jurisdictions: moving from occupation-level projections to task-level, scenario-driven modelling that can stress-test technology adoption, demographic shifts, and policy levers.

Labor Market Granularity: No country currently collects task- or skill-level descriptors within the core LFS; instruments remain anchored in occupational codes. As shown in Exhibit 2, about half of the countries sit at level 2, reporting labor market statistics at occupational levels with ISCO 3-4 digits or equivalent. The U.S. shows what deeper granularity looks like outside the statistical system: O*NET provides detailed task and skill descriptors with intensity/proficiency levels and associated wages, updated on a quarterly basis.[56] However, O*NET operates in parallel and is not embedded in labor surveys. Similarly, Canada's Occupational and Skills Information System (OaSIS) mirrors O*NET-style content, but official indicators largely remain at occupational aggregates. Australia illustrates a pragmatic integration path: although the LFS reports occupations at ANZSCO 4-digit, Jobs and Skills

---

47 Bureau of Labor Statistics (n.d.), "Employment Projections". Available at: https://www.bls.gov/data/home.htm#projections

48 Government of Canada (n.d.), "Canadian Occupational Projection System (COPS)". Available at: https://occupations.esdc.gc.ca/sppc-cops/w.2lc.4m.2%40-eng.jsp

49 Federal Institute for Vocational Education and Training (n.d.), "The QuBe Data Portal". Available at: https://www.bibb.de/en/qube_datenportal.php#/

50 European Centre for the Development of Vocational Training (2025), "Skills forecasts country reports ". Available at: https://www.cedefop.europa.eu/en/country-reports/skills-forecasts

51 Haut-commissariat à la Stratégie et au Plan (2022), "Occupations in 2030". Available at: https://www.strategie-plan.gouv.fr/en/publications/occupations-2030

52 Skills England (2025), "Assessment of priority skills to 2030".
Available at: https://www.gov.uk/government/publications/assessment-of-priority-skills-to-2030/assessment-of-priority-skills-to-2030#introduction

53 KSA National Labor Observatory (2025), "National Occupational Outlook 2025-2034". Available at: https://nlo.gov.sa/landing/reports/report-details/642?lang=en

54 Skills Future SG (2025), "Skills Demand for the Future Economy Report". Available at: https://jobsandskills.skillsfuture.gov.sg/sdfe-2025

55 Ministry of Human Resources & Emiratisation (2025), "MoHRE sets benchmark for digital innovation, showcasing a range of smart services at GITEX Global 2025".
Available at: https://www.mohre.gov.ae/en/media-center/news/10/10/2025/mohre-sets-benchmark-for-digital-innovation-showcasing-a-range-of-smart-services-at-gitex-global

56 O*NET(n.d.), "O*NET 30.0 Database". Available at: https://www.onetcenter.org/database.html

Australia fuses LFS, census, and other sources to generate task-level views—creating capacity to reflect emerging changes without overloading the survey.[57]

Several countries have already updated their national skills taxonomy to match the developments of AI. Japan published its Digital Skills Standards in 2022 as a national guide for digital transformation and human capital development. The Standards were subsequently revised in 2023 and 2024 to reflect the emergence of generative AI in the underlying skills components.[58] Similarly, Singapore developed its Skills Framework for Infocomm Technology in 2017 to map the skills needed for a career in information and communication technology (ICT). The Framework is regularly refreshed, with the most recent update made in March 2025 to include generative AI technical skills and competencies for both AI users and practitioners.[59] While these taxonomies have not been embedded directly within core labor force statistics, they demonstrate a pragmatic route for countries to keep national skills systems aligned with rapid technological change.

Accessibility: Access regimes materially shape what the ecosystem can build. At the frontier (level 4), Finland, the United Kingdom, the U.S., and Spain provide fully open, machine-readable, API-enabled access—lowering friction for reproducible analysis and third-party tools. About half of the countries analyzed are categorized as level 3, offering partial openness, with machine-readable microdata tables available for public or research use. For example, Canada restricts microdata on government portals but enables downloads via approved academic platforms, like Abacus Data Network.[60] South Africa publishes microdata for public access in a range of machine-readable formats that support research and analysis, including comma separated values (CSV), SPSS, SAS, and Stata.[61] Additionally, LFS microdata for several EU countries is published on Eurostat in Excel format only.[62] Level 2 systems center on reports and aggregate/tabulated series; microdata is not openly available, and APIs—where they exist—typically expose only aggregates (e.g., Japan's API provides tabulated data only).[63] KSA has enabled APIs in its statistics system, but does not yet provide access to labor market microdata.[64]

Interoperability: Adoption of common classifications and robust crosswalks determines how easily data travels across systems and borders. Level 4 countries demonstrate strong alignment: either direct use of ISCO or comprehensive crosswalks that enable consistent mapping across statistical products and partner datasets. A broad set of level 3 countries maintains substantial interoperability (e.g., ISCO/U.S. SOC alignment, documented mappings), but linkages are not uniformly implemented across outputs. In practice, EU labor-force statistics benefit

---

57 For example, for occupation accountants, the data source includes LFS, Census, and Survey of Employee Earnings and Hours. Available at: https://www.jobsandskills.gov.au/data/occupation-and-industry-profiles/occupations/2211-accountants

58 Information-technology Promotion Agency, Japan (2024), "The Digital Skill Standards". Available at: https://www.ipa.go.jp/jinzai/skill-standard/dss/eid2eo00000087hx-att/eiyaku.pdf

59 Infocomm Media Development Authority (2025), "Skills Framework for Infocomm Technology (SFw for ICT)". Available at: https://www.imda.gov.sg/how-we-can-help/techskills-accelerator-tesa/skills-framework-for-infocomm-technology-sfw-for-ict

60 Abacus (2025), "Labour Force Survey 2025". Available at: https://abacus.library.ubc.ca/dataset.xhtml?persistentId=hdl:11272.1/AB2/CRDZJ0

61 Statistics South Africa (2025), "Quarterly Labour Force Survey 2025 - Datasets". Available at: https://isibaloweb.statssa.gov.za/pages/surveys/pss/qlfs/2025/qlfs2025.php

62 Eurostat (n.d.), "Labour force survey". Available at: https://ec.europa.eu/eurostat/web/microdata/public-microdata/labour-force-survey

63 E-Stat (2025), "Labour Force Survey." Available at: https://www.e-stat.go.jp/en/stat-search/files?page=1&query=Labour%20Force%20Survey&layout=dataset&metadata=1&data=1

64 General Authority of Statistics (n.d.), "Batch Data". Available at: https://dp.stats.gov.sa/batch-data

from ISCO-based collection, streamlining cross-country comparison. The U.S. maintains extensive crosswalks in O*NET, including international standards ESCO and U.S. SOC, yet these bridges are not systematically embedded into official labor statistics series.[65] Australia similarly documents alignments between the Occupation Standard Classification for Australia (OSCA) and ISCO-08, supported by published correspondence tables that enable consistent mapping across classification systems.[66]

Looking forward, Finland has proposed a WorldSkills occupational standards that offer an interoperability lever: publicly available, regularly updated task-level benchmarks that serve as a common reference for national and regional qualification frameworks and can facilitate crosswalks between competencies and occupational classifications across systems.[67]

Integration: Many countries are progressing from pilots to structured arrangements, but integration into official indicators remains uneven. Level 3 countries operate formal data-sharing channels or APIs and routinely join public and private feeds—yet outputs are often published as standalone dashboards or reports rather than embedded in national labor-statistical series. For example, France strengthened employment services through public-private partnerships by opening up its public employment service website, France Travail, in 2013 to aggregate job offers from the public and private sectors on the website.[68] This model reduces latency and improves coverage of job postings to better support job matching. While the data is made accessible to all individuals and businesses via an open API, it is still not directly integrated within national labor statistics.[69] South Korea enables exchanges between Employment24 and major private portals (Job Korea, Saramin, Incruit) to improve matching services.[70] The Ministry of Data and Statistics (KOSTAT) big-data strategy emphasizes incorporating private data, though full implementation is pending.[71] Level 2 countries generally rely on ad-hoc research partnerships with little routine ingestion of private data into official labor indicators. Several countries have the legal or technical foundations in place but have yet to operationalize them. KSA, for example, has established policies that enable public–private data sharing—positioning the system for future integration—even though private data is not yet incorporated into labor statistics today.[72] At level 1, the U.S. and Japan make limited use of private data in public statistics. In the U.S., however, nonprofit initiatives—such as the NLx Research Hub—have already moved ahead by aggregating real-time employer postings for research at scale, signaling that the value of this data is recognized even if it is not yet embedded in federal series.[73]

65 O*NET (n.d.), "O*Net OnLine". Available at: https://www.onetonline.org/

66 Australian Bureau of Stastics (2024), "Comparison with ISCO-08".
Available at: https://www.abs.gov.au/statistics/classifications/osca-occupation-standard-classification-australia/2024-version-1-0/comparison-isco-08

67 Skills Finland (2025), "Towards a better world through WorldSkills occupational standards". https://www.skillsfinland.fi/eng/blogs/towards-a-better-world-through-worldskills-occupational-standards

68 International Labour Organization (2023), "France: Human-centred public-private cooperation for strengthening employment services".
Available at: https://www.ilo.org/resource/news/france-human-centred-public-private-cooperation-strengthening-employment

69 Datagouv (n.d.), "API Job Offers". Available at: https://www.data.gouv.fr/dataservices/api-offres-demploi/

70 Sources include: OECD (2024), "Strengthening Active Labour Market Policies in Korea". Available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/06/strengthening-active-labour-market-policies-in-korea_2d84239b/44cb97d7-en.pdf; and Korea Employment Information Service (n.d.), "'Employment24' Digital Employment Services".
Available at: https://m.keis.or.kr/keis/en/conts/283/web.do

71 International Association for Official Statistics (2016), "Big Data Strategy of Statistics Korea". Available at: https://iaos-isi.org/wp-content/uploads/2023/03/haeryun_kim_presentation.pdf

72 Saudi Data and AI Authority (2024), "Data Sharing Policy". Available at: https://sdaia.gov.sa/en/SDAIA/about/Documents/DataSharingPolicyEN.pdf

73 NLx Research Hub (n.d.). Available at: https://nlxresearchhub.org/

Real-time Responsiveness: 57% of systems operate at level 4, conducting LFS on a monthly basis. Coupled with machine-readable access and consolidated vacancies/administrative feeds, this cadence enables near real-time nowcasts and rapid stress testing. Another 38% update their LFS each quarter (level 3), which is timely, but increasingly exposed to missed inflection points in occupations and skills amid AI-driven shifts. Across the analysis, only the UAE remains on an annual cycle (level 2), creating material visibility gaps between survey rounds and increasing the risk of missing fast-moving labor market dynamics, especially in the era of AI.

BOX 1 **Frontier profiles in AI-ready labor data systems**

A small set of countries consistently score well across the FLAIR dimensions, illustrating what an AI-ready labor data system can look like. Finland sits at the frontier: it combines long horizon forecasting, high-frequency labor force data, strong interoperability, and fully open, machine-readable access—making it one of the closest examples of an AI-ready, task- and skill-aware labor data system. The UK also performs strongly across most dimensions, pairing robust interoperability and openness with monthly LFS collection and well-developed APIs that enable downstream use by researchers and third-party tools. Similar, though slightly more uneven, high-performing profiles can be seen in Italy, Denmark, Norway, Sweden, and the U.S., which generally combine frequent labor force data collection with relatively strong accessibility and interoperability.

Crucially, no country in the sample attains level 4 across all six FLAIR dimensions. Even the strongest performers exhibit gaps—whether in task- and skill-level granularity, integration of private data, or end-to-end use of AI-enabled forecasting. This highlights that all countries still have substantial room to advance toward fully AI-ready labor data systems.

In summary, the cross-country benchmarking reveals strong foundations but uneven maturity across the FLAIR dimensions. Most advanced economies deliver level 3 forecasting and level 4 timeliness, yet granularity remains anchored in occupational codes, and private data integration is still project-based rather than production-grade. Leaders on accessibility and interoperability (e.g., Finland, the UK, the U.S., Canada) show how open, machine-readable data and robust crosswalks lower friction for analysis, while Germany's long-horizon projections and France vacancy APIs illustrate the path from static reports to decision-ready pipelines. The main execution gap is stitching these assets together: linking monthly LFS cadence with vacancy and administrative streams, applying standardized task/skill taxonomies, and operationalizing public-private data sharing so private signals flow into official indicators by default. Jurisdictions that close this loop will move first from retrospective reporting to anticipatory, skills aware labor governance, with clearer visibility on fast-moving occupational and skill dynamics in the AI era.

4. Policy recommendations

The cross-country assessment in Chapter 3 highlights that while many countries have established solid foundations for labor market monitoring, none possesses the end-to-end data architecture required to navigate an AI-driven economy. Existing systems remain predominantly descriptive and occupation-based, limiting policymakers' ability to anticipate technological disruption or respond effectively to emerging skills demands. Addressing these gaps will require not only incremental improvements but a coordinated shift toward more granular, interoperable, and real-time labor market intelligence, translating signals into better decisions that support employers, job seekers, and incumbent workers through improved skills matching, reduced hiring frictions, and faster access to targeted training and transition support.

This chapter therefore translates the FLAIR maturity framework into a set of concrete policy recommendations. It defines the features of an aspirational, AI-ready labor data system and outlines a sequenced transition pathway with short-, medium-, and long-term actions that countries can adopt to progressively strengthen forecasting capability, granularity, accessibility, interoperability, private data integration, and real-time responsiveness. The aim is to provide governments with a practical roadmap for evolving from fragmented practices to a resilient labor data infrastructure fit for the speed and complexity of the AI era.

4.1. Aspirational labor market data structure

Based on the FLAIR framework, a fully mature and AI-ready labor-market data system would meet level-4 performance across all indicators:

- **Forecasting readiness:** Incorporates labor forecasts using scenario-based modelling in existing labor market data to better anticipate changes in an AI-driven economy.
- **Labor market granularity:** Includes both task- and skill-level data with varying intensity or proficiency levels, as well as subnational (regional and local) geographic details, to assess the type of skills that are most in demand, and conversely, those that will be substituted by AI.
- **Accessibility:** Fully open-source microdata in machine-readable and API-enabled formats to enable researchers and the private sector to gain a deeper understanding of the changes and highlight them to the government.
- **Interoperability:** Ensures that national classification is harmonized with international standards to enable better comparison and understanding of how the labor market responds to different policies.
- **Integration:** Routinely supplements current data with rich and diverse private datasets to improve the quality and information of labor data. This also reduces public resources needed to collect additional data by leveraging the private sector's expertise.
- **Real-time responsiveness:** Provides near real-time updates of data to keep pace with the fast changes caused by AI.

This represents an aspirational benchmark rather than an immediately attainable standard. Nonetheless, given the speed and scale of AI-related labor market change, progressing toward this model is essential for strengthening national resilience, competitiveness, and policy agility.

4.2. Actions toward an AI-ready labor data system

Building an AI-ready labor-market data system requires coordinated action across four broad areas. These areas reflect the essential building blocks of a modern labor-data ecosystem—from what countries collect and how systems are structured, to how insights are generated and how institutions collaborate and govern the use of data (Exhibit 3).

- **Data Collection** is the starting point, determining what is known about jobs, tasks, skills, and technology use, and where these changes are occurring geographically. Enhancing this area means updating survey instruments, leveraging new data sources, and ensuring that collected data can capture how work is changing inside occupations across regions and local labor markets.
- **System Foundations** focus on the technical and structural conditions that allow labor-market data to function as a coherent system. This includes improving data standards, ensuring interoperability, upgrading digital infrastructure, and enabling secure data sharing and accessibility.
- **Intelligence Capabilities** involve turning diverse data sources into forward-looking insights that help governments anticipate labor market shocks. This requires strengthening forecasting tools, integrating high-frequency private-sector data, and improving the timeliness of labor market indicators.
- **Governance and Partnerships** provide the institutional arrangements that ensure reforms take root and remain aligned over time. This encompasses national leadership, multi-stakeholder coordination, ethical safeguards, and international cooperation on shared standards and foresight tools.

Exhibit 3: Overview of policy recommendations

Essential areas of reform	Policy actions
Data Collection	Action 1: Modernize labor force survey instruments and administrative datasets to capture a wider range of variables. Action 2: Design data-collection strategies to support forward-looking analysis rather than purely descriptive reporting. Action 3: Leverage new technologies to enhance current data collection practices.
System Foundations	Action 4: Jointly develop a common task- and skill-level taxonomy that can be embedded into labor force surveys. Action 5: Modernize data infrastructure to ensure full accessibility and analytical utility. Action 6: Regularly update and systematically apply crosswalks across labor statistics.

Intelligence Capabilities	Action 7: Make data collection and reporting more continuous and adaptive to enable near real-time labor market monitoring. Action 8: Develop common modelling scenarios and tools and institutionalize them within labor projections. Action 9: Establish public-private partnerships to integrate alternative data into labor statistics.
Governance and Partnerships	Action 10: Governments should take the lead role in enhancing labor market data systems. Action 11: Encourage voluntary public-private partnerships to enhance labor market data. Action 12: Institutionalize multi-stakeholder governance and feedback loops for labor-market data systems.

Taken together, these four elements identify the priority areas where countries can act to operationalize the FLAIR framework and develop labor-market data systems that are more granular, agile, and anticipatory. The sections that follow detail policy actions within each element to help countries advance toward full FLAIR readiness.

4.2.1 Data collection

Data collection forms the foundation of an AI-ready labor-market data system. It determines what is visible about jobs, tasks, skills, and technology use, thereby shaping every analytical and policy decision that follows. Strengthening this layer will require three policy actions for improving labor market granularity, integrating private data, and enabling more credible forecasting.

Action 1: Modernize labor force survey instruments and administrative datasets to capture a wider range of variables. Today, most countries record where people work and in what occupation, but not what tasks they perform, what tools and digital systems they rely on, or how AI reshapes their day-to-day responsibilities. In addition, many labor force and administrative records do not capture information at sufficient subnational detail to distinguish patterns across regions and local labor markets. This limits visibility into within occupation shifts and reduces the ability to track emerging AI-related skills or to distinguish workers with different exposure profiles within the same job family and across different locations. Updating questionnaires to include standard tasks, task-specific skills, digital tools, workers' use of AI, and consistent geographic identifiers (e.g., region, city)—linked to shared taxonomies—can begin to close this gap. To limit compliance costs, these new variables should be designed around information employers already hold in payroll, HR, or accounting systems, with pre-populated fields and collected through digital, low-friction channels where feasible. These can be delivered in short, modular question blocks and paired with emerging technologies such as AI-assisted coding of open-ended job descriptions and automated extraction of structured variables from administrative records.[74] Used appropriately, these tools reduce manual reporting and processing, while improving the timeliness, consistency, and geographic granularity of labor market data.

Action 2: Design data-collection strategies to support forward-looking analysis rather than purely descriptive reporting. Many existing instruments lack the longitudinal structure required for modern, scenario-based labor market projection models. In an AI-driven labor market, credible foresight depends on consistent time series that track how tasks, skills, and technology adoption evolve within occupations and sectors, as well as information on job transitions, contract types, training participation, and other markers of adjustment. Embedding these elements into survey and administrative designs enables forecasting models to simulate how different technological and policy pathways affect skills demand and workforce adjustment. Rather than creating entirely new reporting systems, governments can prioritize the use of existing longitudinal administrative sources—such as unemployment insurance (UI) wage records in the U.S.—by improving linkages, standardizing variables, and expanding access for research and policy analysis.[75] Where additional information is needed, requirements should be phased in and digitally enabled, with priority given to firms already submitting related data. This approach preserves analytical depth while reducing compliance burden and avoiding disproportionate impacts on small and medium-sized enterprises.

Action 3: Leverage new technologies to enhance current data collection practices. Recent developments in AI-enabled market research also illustrate how data collection practices themselves can be modernized. Emerging methods such as "synthetic personas" and "digital twins" allow researchers to simulate how different segments might respond to questions or concepts before fieldwork, enabling rapid iteration on survey design and compression of timelines and cost.[76] Generative AI techniques, already used in market research to extract structure from unstructured text, can also be utilized to harmonize vacancy postings, job descriptions, and platform records into comparable indicators of skills, tasks, and technology use.[77] When adapted carefully to labor market statistics, these tools can help governments prototype question modules, validate task and skill taxonomies, and test policy scenarios in controlled environments, improving the quality and inclusiveness of subsequent large scale surveys rather than replacing them. By automating classification, validation and linkages across datasets, these tools can reduce processing timelines, improve consistency, and minimize additional reporting burden on employers, particularly small businesses, while strengthening the evidence base for workforce policy.

4.2.2 Systems foundations

System foundations provide technical architecture that enables labor-market data to function as a coherent, interoperable system rather than a collection of isolated datasets. This layer focuses on building the standards,

74 TGM Research (n.d.), "How to Analyze Open-Ended Survey Responses with AI". Available at: https://www.looppanel.com/blog/open-ended-survey-responses-ai

75 National Academies (2023), "Toward a 21st Century National Data Infrastructure: Enhancing Survey Programs by Using Multiple Data Sources (2023) Chapter 4: Creating New Data Resources with Administrative Records". Available at: https://www.nationalacademies.org/read/26804/chapter/6#86

76 Jeremy Korst, Stefano Puntoni, and Olivier Toubia (2025), "The AI Tools That Are Transforming Market Research". *Harvard Business Review.* Available at: https://hbr.org/2025/11/the-ai-tools-that-are-transforming-market-research

77 Kaiser et al. (2024), "Generative AI in Market Research". Nuremberg Institute for Market Decisions. Available at: https://www.nim.org/en/publications/detail/generative-ai-in-market-research

classifications, and digital infrastructure required for countries to integrate diverse data sources, apply advanced analytics, and support secure, seamless public–private collaboration. Strengthening this layer requires three policy actions to enhance real-time responsiveness, high-frequency forecasting, and consistent cross-country comparability—capabilities that are increasingly essential in an AI-driven labor market.

Action 4: Jointly develop a common task- and skill-level taxonomy that can be embedded into labor force surveys. Across all countries analyzed, labor statistics remain constrained by occupation-level descriptors. No country has yet formalized task-level measurement in its LFS, presenting a global opportunity for coordinated modernization. Existing frameworks such as O*NET and Canada's OaSIS can provide reference architectures that could be adapted to support cross-country coherence. Governments have a central role to play in convening stakeholders, aligning taxonomies, and setting common data structures and standards, ensuring that emerging task- and skill-level classifications are compatible with national statistical systems and international frameworks. Shared taxonomies not only improve comparability of data across countries but also enable more advanced global analysis and help policymakers measure differential exposure to AI adoption.

Action 5: Modernize data infrastructure to ensure full accessibility and analytical utility. Only a minority of countries (four out of the sample of 21 countries analyzed) currently provide open microdata that is machine-readable and accessible through API. Modernizing data infrastructures is therefore essential to enable automation, integration, and advanced analytics. Transitioning to standardized, API-enabled data platforms—supported by automated ingestion, version control, and scalable processing—creates the technical foundation required for integrating high-frequency and private sector sources. Countries with more restrictive access regimes can begin by releasing selected anonymized datasets in common, machine-readable formats in the interim as they develop their data infrastructure.

Action 6: Regularly update and systematically apply crosswalks across labor statistics. Interoperability is the final and most immediately achievable component of system foundations. With many countries already maintaining formal crosswalks to international standards, the priority now is regular updating and systematic application across all labor statistics. Countries without established mappings should urgently develop crosswalks to international frameworks such as ISCO or U.S. SOC. Maintaining up-to-date interoperability not only improves comparability and migration analysis but also simplifies integration with private sector taxonomies and emerging AI-driven classification tools.

4.2.3 Intelligence Capabilities

Intelligence capabilities enable countries to transform labor-market data into forward-looking insights that anticipate how occupations, tasks, and skills will evolve in an AI-driven economy. Building robust intelligence capabilities requires expanding the analytical tools, methodologies, and data partnerships that governments rely on. These capabilities allow countries to identify emerging risks and opportunities early, model the effects of AI adoption, and stress-test labor-market outcomes under different scenarios. Strengthening this layer further enhances real-time responsiveness, high-frequency forecasting, and integration with private data.

Action 7: Make data collection and reporting more continuous and adaptive to enable near real-time labor-market monitoring. Even among advanced economies, labor statistics often lag months behind market conditions, limiting policymakers' ability to respond proactively to AI-driven changes. To keep pace with these changes over the long run, countries should assess and identify additional labor indicators that would be suitable for more frequent updates, or even real-time updates. Even where LFS are run monthly, they can still miss early inflection points in occupations or skills when AI-related demand shifts within weeks or even days. High-frequency administrative feeds, short mobile or web-based micro-surveys, and platform telemetry can complement monthly LFS cycles, improving nowcasting accuracy and providing earlier signals of shifting skills demand or employment patterns.

Action 8: Develop common modelling scenarios and tools and institutionalize them within labor projections. Today, most countries produce medium- to long-term labor and skills projections, but few incorporate task-level technological change or scenario-based foresight. As a result, official outlooks often lag behind shifts in skill composition, automation pressure, and new AI-enabled occupations. To keep pace, governments must adopt forecasting models and tools that integrate task-level information, historical trends, and multiple AI adoption scenarios. These models allow policymakers to assess where mismatches may emerge, which occupations are most exposed, and what training investments will be required. Looking ahead, countries can co-develop shared scenarios, methodological assumptions, and analytical tools to institutionalize foresight within official projections.

Action 9: Establish public-private partnerships to integrate alternative data into labor statistics. As Chapter 2 highlighted, no single dataset can capture the full spectrum of AI-era occupational change; private data is often where new roles, new skill bundles, and non-standard forms of work appear first. Digital labor platforms, HRIS providers, and job posting analytics firms generate rich, high-frequency data on skills demand, workforce transitions, and hiring behavior. The U.S. Department of Labor, for example, has taken actions to establish an AI Workforce Research Hub to deliver recurring analysis, scenario planning, and actionable insights on how AI is affecting the labor market and workers, which is expected to benefit from data-sharing partnerships with leading AI developers and payroll and hiring platforms.[78, 79] Countries with no prior engagement can start by exploring private sources and assessing the impact of such integration before formalizing further partnerships. While most other countries already have some private data sharing agreements in place, these are limited to select labor indicators like job vacancies. These arrangements could evolve to include more comprehensive data, such as skill demands of job vacancies, to better adapt to AI changes.

---

78 U.S. Department of Labor (2025), "US Department of Labor applauds President Trump's 'AI Action Plan' to achieve global dominance in artificial intelligence". Available at: https://www.dol.gov/newsroom/releases/osec/osec20250723

79 Sam Manning, (2025), "Understanding AI's Labor Market Impacts: Opportunities for the Department of Labor's AI Workforce Research Hub", Foundation for American Innovation. Available at: https://www.thefai.org/posts/understanding-ai-s-labor-market-impacts-opportunities-for-the-department-of-labor-s-ai-workforce

4.2.4 Governance and Partnerships

Governance and partnerships represent the institutional architecture that oversees and anchors labor market data reforms. Building strong governance and partnership arrangements ensures that reforms to data collection, system foundations, and intelligence capabilities are embedded, scaled, and aligned. These arrangements provide continuity across electoral cycles, clarify roles for government, industry, and MLOs, and establish safeguards around privacy and ethical data use. Together, they enable countries to systematically integrate diverse data sources, maintain shared standards, institutionalize forecasting, and sustain granular, task- and skill-level measurement as core features of labor market governance.

Action 10: Governments should take the lead role in enhancing labor-market data systems. As the primary guarantor of public interest, it must establish the legal, institutional, and technical foundations that determine how labor data is collected, governed, shared, and used. This includes modernizing statistical infrastructure, expanding LFS to incorporate task- and skill-level information, and ensuring that datasets are published in machine-readable, interoperable formats. Governments also set the policy frameworks that govern privacy, ethical use, data security, and long-term data stewardship—ensuring trust, accountability, and equitable access across society.

Effective governance further requires clear institutional mandates. By designating national statistical offices or equivalent bodies to oversee labor data reform, governments can coordinate across ministries, education systems, and public employment services, aligning data modernization with workforce, industrial, and innovation strategies. Governments also play a critical role in establishing structured partnerships with industry and research institutions, enabling responsible data sharing, model development, and validation.

Action 11: Encourage voluntary public-private partnerships to enhance labor market data. The private sector plays a critical role in closing the information gap that traditional LFS and administrative systems cannot fill. Private sector platforms collect vast volumes of real-time data on vacancies, skills demand, job transitions, and work practices. Where feasible, these high-frequency signals can be incorporated through voluntary partnerships, complementing official statistics with early indicators of technological adoption, emerging occupations, and changing skill profiles—without imposing mandatory reporting burdens on firms.

Beyond improving timeliness and granularity, voluntary public-private partnerships also enable methodological innovation: private datasets can support the development of task-level taxonomies, training datasets for AI-enabled classification tools, and nowcasting models that integrate vacancy postings, HRIS feeds, and mobility signals. When governed properly through structured data sharing agreements, privacy-preserving APIs, and common data trust frameworks, these datasets can significantly strengthen governments' ability to forecast workforce needs, target reskilling investments, and monitor structural change while protecting confidentiality and commercial sensitivities.

Governments can incentivize public-private partnerships and voluntary cooperation by offering financial compensation and through non-financial reciprocity mechanisms, for example via shared platforms, whereby participating firms are provided access to skills forecasts, curated datasets, or advanced analytical tools in exchange for contributing high-frequency labor data.

Action 12: Institutionalize multi-stakeholder governance and feedback loops for labor-market data systems. Governments should establish formal governance arrangements—such as standing labor market data councils or advisory boards—that bring together employers, worker representatives, training and education providers, researchers, and civil society. For example, the U.S. BLS Data Users Advisory Committee brings together data users from various sectors to surface priority gaps and merging needs for the BLS.[80] These bodies can help set priorities for new indicators, review proposed task- and skill-level taxonomies, and provide structured feedback on how data is used in workforce, industry, and education policy.

Institutionalized governance should also embed regular review and learning cycles for the labor data system itself. This includes publishing transparent documentation of data sources and methods, commissioning periodic independent evaluations of forecasting models and data linkages, and creating channels for users to flag blind spots or unintended impacts (for example, on specific regions or groups of workers). The UK Office for Statistics Regulation, for instance, has conducted periodic reviews of the labor market statistics from LFS.[81] By moving from ad hoc consultation to a stable, multi-stakeholder governance model, governments can ensure that labor market data systems remain legitimate, demand-driven, and adaptable as AI reshapes work.

[80] Federal Register (2024), "Data Users Advisory Committee; Renewal of the Bureau of Labor Statistics Data Users Advisory Committee". Available at: https://www.federalregister.gov/documents/2024/09/20/2024-21526/data-users-advisory-committee-renewal-of-the-bureau-of-labor-statistics-data-users-advisory

[81] Office for Statistics Regulation (2025), "Statistics from the Labour Force Survey". Available at: https://osr.statisticsauthority.gov.uk/publication/statistics-from-the-labour-force-survey/

5. Appendix

Appendix A: Methodology for cross-country analysis based on the FLAIR framework

We assess labor market data maturity across 21 countries using the FLAIR framework. Each indicator is scored on a 1–4 scale, with anchors tailored to that indicator's construct and the specific evidence available (see Exhibit A1). Because indicators and underlying data sources differ, the scoring criteria are indicator-specific and therefore not directly comparable across indicators; comparisons should be made within an indicator across countries. Evidence was drawn from official publications and the websites of national statistical offices and labor/employment ministries. Our assessment focuses on national-level systems; sub-national data and non-government data are not considered.

Exhibit A1: FLAIR framework assessment criteria

	Forecasting Readiness	Labor Market Granularity	Accessibility	Interoperability	Integration	Real-time Responsiveness
Data or reports evaluated	Government reports or government projection data	LFS	LFS	LFS or occupation classification	National workgroup or plans to cooperate with private data	LFS
Scale 1	Only descriptive statistics of the current labor market or skills level are provided.	Occupational data is collected at ISCO 1 or 2 digits, or equivalent only.	Microdata is not accessible to the public.	No crosswalks or harmonization between national and international occupation classification. National occupation data cannot be compared with other countries.	No evidence of private data usage.	Labor statistics are updated only once every 5 years or longer.
Scale 2	Short-term (1-2 years) projections of labor or skills outlook are published, either from statistics agencies or government studies.	Occupational data is collected at ISCO 3 or 4 digits, or equivalent only.	Microdata is only available through public reports or tabulated data (e.g., aggregated tables of LFS results).	Only crosswalks between national and international classification exist for certain occupations.	Some studies leveraging private data were conducted and published by government agencies.	At least one labor statistic (e.g., unemployment rate) is published and updated annually.

Scale 3	Medium- to long-term (3 years or more) projections of labor or skills outlook are published, either from statistics agencies or government studies.	Occupational data is collected with some task or skill descriptions included.	Either microdata is accessible but limited to certain file types only, or microdata in various file types is accessible to researchers only.	Formal crosswalks exist between national and international classifications. However, the crosswalks are either not systematically applied to all statistics or are not updated regularly to reflect ongoing changes.	There are some arrangements to integrate private data with public data. However, these arrangements are only limited to certain indicators (e.g., job vacancies). The data is also not integrated into labor statistics but is shared in separate dashboards.	At least one labor statistic (e.g., unemployment rate) is published and updated quarterly.
Scale 4	AI-enabled foresight tools, or task/skill-level modelling published.	Detailed task and skill data for each occupation with proficiency levels collected.	Microdata is accessible to the public in various file types or through API access.	Either formal crosswalks exist and are regularly updated, or countries have fully adopted international classifications.	Private data is integrated with public data and reported together with labor statistics. There is a comprehensive list of data incorporated, including skills and occupations data.	At least one labor statistic (e.g., unemployment rate) is published and updated monthly.

Appendix B: Official sources and reference documents underpinning countries' FLAIR score

This section compiles the official documents, datasets, and reference materials used to assess each country against the scoring scales for elements of the FLAIR framework. Sources are organized for each country and mapped to the relevant FLAIR dimensions, indicating the primary evidence that informed each score. The evidence prioritizes government and statutory publications (e.g., labor ministries, national statistics offices, public employment services, and national skills agencies), complemented where necessary by research institutes and private sector publications to support consistent comparison.

Australia

- **Forecasting readiness:** Jobs and Skills Australia employment projections by Australian government
- **Labor Market Granularity:** Australian Bureau of Statistics – Labour Force, Australia, Detailed; Jobs and Skills Australia Occupation and Industry Profiles by Australian Government
- **Accessibility:** Australian Bureau of Statistics – Indicator API with tabulated data available
- **Interoperability:** Australian Bureau of Statistics – Occupation Standard Classification for Australia (OSCA)
- **Integration:** Jobs and Skills Australia Internet Vacancy Index Methodology by Australian government
- **Real-time responsiveness:** Australian Bureau of Statistics – Labour Force Survey

Belgium

- **Forecasting readiness:** 2025 skills forecast Belgium by European Centre for the Development of Vocational Training (Cedefop)
- **Labor Market Granularity:** Labour Force Survey by the Belgian statistical office (STATBEL)
- **Accessibility:** Microdata of Labour force survey by Eurostat
- **Interoperability:** Labour Force Survey by STATBEL
- **Integration:** Ad hoc research, for example, 2025 skills forecast Belgium by European Centre for the Development of Vocational Training (Cedefop)
- **Real-time responsiveness:** Labour force survey - purpose and short description by STATBEL

Canada

- **Forecasting readiness:** Canadian Occupational Projection System (COPS) by Government of Canada
- **Labor Market Granularity:** Guide to the labor force survey by Statistics Canada
- **Accessibility:** Abacus data network
- **Interoperability:** Concordances between classifications by Statistics Canada
- **Integration:** Government-funded partnership, Canadian Job Trends Dashboard
- **Real-time responsiveness:** Labour force survey by Statistics Canada

Denmark

- **Forecasting readiness:** Labour market projection by Danish Research Institute for Economic Analysis and modelling
- **Labor Market Granularity:** Commission implementing regulation (EU) 2019/2240, EN Official Journal of the European Union
- **Accessibility:** Data for research by Statistics Denmark; Microdata of Labor force survey by Eurostat
- **Interoperability:** Statistics Denmark's Classification of Occupations (DISCO-08), v1:2010
- **Integration:** Analyse af arbejdskraftsefterspørgslen ved hjælp af jobopslag by Højbjerre Brauer Schultz
- **Real-time responsiveness:** the monthly labour force survey relevance by Statistics Denmark

Finland

- **Forecasting readiness:** labour market forecasts by Ministry of Economic Affairs and Employment; 2025 skills forecast Finland by Cedefop
- **Labor Market Granularity:** Labour force survey: documentation of statistics, by Statistics Finland
- **Accessibility:** PxWeb API for Statistics Finland databases
- **Interoperability:** Classification of Occupations 2010, by Statistics Finland
- **Integration:** Job Market Finland service platform
- **Real-time responsiveness:** Labour force survey, by Statistics Finland

France

- **Forecasting readiness:** Occupations in 2030, by Haut-commissariat à la Stratégie et au Plan; 2025 skills forecast France by Cedefop
- **Labor Market Granularity:** No employment data at the detailed occupation level
- **Accessibility:** Labour Force Survey 2025, by National Institute of Statistics and Economic Studies (INSEE)
- **Interoperability:** Télécharger les tables de correspondance entre la PCS 2020 et ISCO, by National Institute of Statistics and Economic Studies (INSEE)
- **Integration:** France: Human-centred public-private cooperation for strengthening employment services by ILO; API Offres d'emploi by La plateforme des données publiques françaises
- **Real-time responsiveness:** Labour force survey by National Institute of Statistics and Economic Studies (INSEE)

Germany

- **Forecasting readiness:** The Sixth Wave of Qualifications and Occupation Projections From the Year 2020 by Federal Institute for Vocational Education and Training
- **Labor Market Granularity:** Lack of data by occupation codes. Employees subject to social insurance contributions by occupational activity by the Federal Statistical Office of Germany
- **Accessibility:** Metadaten by Statistisches Bundesamt; Microdata of Labor force survey by Eurostat
- **Interoperability:** The Coding of Occupations by Leibniz Institute for the Social Sciences (GESIS)
- **Integration:** Ad hoc partnerships, for example, Impact of the coronavirus crisis on the labor market: experimental statistics based on data from online job portals
- **Real-time responsiveness:** Frühindikatoren für den Arbeitsmarkt - Deutschland, Länder, Agenturen und Kreise (Monatszahlen) by Federal Employment Agency

Ireland

- **Forecasting readiness:** Job and skill forecasting reports by SOLAS
- **Labor Market Granularity:** No employment data at the detailed occupation level
- **Accessibility:** PxStat and Anonymised Microdata Files for Researchers by Central Statistics Office
- **Interoperability:** Census of Population 2022 by Central Statistics Office
- **Integration:** Ad hoc research, for example, Skill Requirements for Emerging Technologies in Ireland
- **Real-time responsiveness:** Labour Force Survey by Central Statistics Office

Italy

- **Forecasting readiness:** 2025 skills forecast Italy by Cedefop
- **Labor Market Granularity:** Labour Force Survey Microdata by Istituto Nazionale di Statistica (Istat)
- **Accessibility:** Microdata of Labour force survey by Eurostat
- **Interoperability:** Classification of occupations by Istituto Nazionale di Statistica (Istat)
- **Integration:** Backed by the Government: How Lightcast is Fueling Italy's National Workforce Strategy by Lightcast
- **Real-time responsiveness:** Labour Force Survey Microdata by Istituto Nazionale di Statistica (Istat)

Japan

- **Forecasting readiness:** No official forecast available
- **Labor Market Granularity:** Labour Force Survey Basic Tabulation Whole Japan Monthly by Statistics of Japan
- **Accessibility:** Labour force survey data by Statistics of Japan
- **Interoperability:** Japan Standard Occupational Classification by Ministry of Internal Affairs and Communications
- **Integration:** No records available
- **Real-time responsiveness:** Labour force survey 2020 by ILOSTAT

The Kingdom of Saudi Arabia (KSA)

- **Forecasting readiness:** KSA Employment Outlook Report by National Labor Observatory; National Occupational Outlook 2025-2034 by National Labor Observatory
- **Labor Market Granularity:** Labor Force Survey 2025 Q1 by General Authority for Statistics
- **Accessibility:** Labor Market Statistics by General Authority for Statistics
- **Interoperability:** Methodology of Labor Market Statistics by General Authority for Statistics
- **Integration:** Partnership with LinkedIn - SDAIA and LinkedIn Sign MoU to Study Data and AI Market in Saudi Arabia; Data sharing policy by Saudi Data & AI Authority
- **Real-time responsiveness:** Labor Force Survey Data by KAPSARC Data Portal

Netherlands

- **Forecasting readiness:** 2025 skills forecast Netherlands by Cedefop
- **Labor Market Granularity:** No employment data by occupation code - StatLine
- **Accessibility:** The OData API of Statistics Netherlands provides users access to StatLine data in a machine-readable format
- **Interoperability:** Beroepenclassificatie (ISCO en SBC) by Statistics Netherlands
- **Integration:** Dashboard Online vacatures UWV
- **Real-time responsiveness:** Labour Force Survey by Statistics Netherlands

Norway

- **Forecasting readiness:** Skills Forecast by Cedefop
- **Labor Market Granularity:** Labour force survey by Statistics Norway
- **Accessibility:** Access to microdata by Statistics Norway
- **Interoperability:** Labour force survey by Statistics Norway
- **Integration:** NAV Job Vacancy Feed
- **Real-time responsiveness:** Labour force survey by Statistics Norway

Singapore

- **Forecasting readiness:** Skills Demand for the Future Economy Report by SkillsFuture Singapore
- **Labor Market Granularity:** Labour Force Survey by SingStat
- **Accessibility:** Data for researchers by SingStat
- **Interoperability:** Singapore Standard Occupational Classification (SSOC) 2024 by SingStat
- **Integration:** Jobs Situation Report by Ministry of Manpower
- **Real-time responsiveness:** Labour Force Survey by SingStat

South Africa

- **Forecasting readiness:** Development plan is available, but no occupation, task, or skill specific forecasts
- **Labor Market Granularity:** Quarterly Labour Force Survey 2025 by Statistics South Africa, and Organising Framework Of Occupations (Ofo) Mapping Studies For The Public Service Sector by Public Service Sector Education and Training Authority
- **Accessibility:** Labour Force Survey by Statistics South Africa
- **Interoperability:** Organising Framework Of Occupations (Ofo) Mapping Studies For The Public Service Sector by Public Service Sector Education and Training Authority
- **Integration:** Presidential Youth Employment Intervention by the Presidency Project Management Office
- **Real-time responsiveness:** Labour Force Survey by Statistics South Africa

South Korea

- **Forecasting readiness:** Only macro level outlook is available, not occupation projections
- **Labor Market Granularity:** Labor Force Survey by Ministry of Employment and Labor
- **Accessibility:** Labor Force Survey by Ministry of Employment and Labor
- **Interoperability:** Korean Standard Classification of Occupations by Statistics Korea
- **Integration:** Employment24 by Korea Employment Information Service
- **Real-time responsiveness:** Economically Active Population Survey by Ministry of Data and Statistics

Spain

- **Forecasting readiness:** 2025 skills forecast Spain by Cedefop
- **Labor Market Granularity:** Incluye nombres de variables by Instituto Nacional de Estadística
- **Accessibility:** Microdata by Instituto Nacional de Estadística
- **Interoperability:** La Clasificación Nacional de Ocupaciones 2011 by Instituto Nacional de Estadística
- **Integration:** Empléate job portal by El Servicio Público de Empleo Estatal
- **Real-time responsiveness:** Economically Active Population Survey by Instituto Nacional de Estadística

Sweden

- **Forecasting readiness:** 2025 skills forecast Sweden by Cedefop
- **Labor Market Granularity:** Swedish Standard Classification of Occupations 2012 by Statistikmyndigheten SCB
- **Accessibility:** Statistical database by Statistikmyndigheten SCB
- **Interoperability:** Swedish Standard Classification of Occupations 2012 by Statistikmyndigheten SCB
- **Integration:** Arbetsförmedlingens Datakatalog by Arbetsförmedlingen
- **Real-time responsiveness:** Labour Force Surveys by Statistikmyndigheten SCB

The United Arab Emirates (UAE)

- **Forecasting readiness:** New MoHRE projects and services by Ministry of Human Resources and Emiratisation
- **Labor Market Granularity:** Labour Force Survey by National Bureau of Statistics and Labour Force data by UAEStat
- **Accessibility:** Data and resources by Bayanat
- **Interoperability:** Labour Force Survey by National Bureau of Statistics
- **Integration:** Emirati Smart Human Resource Platform by Emirati Human Resources Development Council and Data for Good Framework by Statistics Centre – Abu Dhabi
- **Real-time responsiveness:** Labour Force Survey by National Bureau of Statistics

The United Kingdom (UK)

- **Forecasting readiness:** Assessment of priority skills to 2030 by Skills England (UK government)
- **Labor Market Granularity:** Supply of skills for jobs in science and technology 2023 by Department for Education; Measuring skill and qualification suitability in the UK labour market: user guide by Office for National Statistics
- **Accessibility:** Quarterly Labour Force Survey, Household Dataset and Developer API Access by UK Data Service
- **Interoperability:** Developing a method for measuring time spent on green tasks: March 2022 by Office for National Statistics
- **Integration:** Textkernel new online job adverts by Office for National Statistics
- **Real-time responsiveness:** Labour market overview, UK Statistical bulletins by Office for National Statistics

The United States (U.S.)

- **Forecasting readiness:** Employment projections by U.S. Bureau of Labor Statistics (BLS)
- **Labor Market Granularity:** Employment data by BLS
- **Accessibility:** BLS Public Data API
- **Interoperability:** Classifications and Crosswalks by BLS; O*NET has more comprehensive crosswalks
- **Integration:** NLx Research Hub
- **Real-time responsiveness:** Current Employment Statistics by BLS

General use restriction

This report has been prepared by Access Partnership for Workday. We accept no duty of care to any other person or entity. The report has been prepared for the purpose of providing an analysis of labor data readiness in the age of AI.

All information in this report is derived or estimated by Access Partnership using both proprietary and publicly available information. Workday has not supplied any additional data, nor does it endorse any estimates made in this report. Where information has been obtained from third-party sources, this is referenced within.

Access Partnership

accesspartnership.com

Follow us

Our offices

Europe

London

The Tower, Buckingham Green
Buckingham Gate
London, SW1E 6AS
United Kingdom

+44 20 3143 4900
london@accesspartnership.com

Brussels

8th Floor, Silversquare Europe
Square de Meeûs 35
B-1000 Brussels
Belgium

brussels@accesspartnership.com

North America

Washington DC

1300 Connecticut Avenue NW,
Suite 250
Washington, DC 20036
USA

+1 202 503 1570
washingtondc@accesspartnership.com

Asia

Singapore

Asia Square, Tower 2
#11-20
12 Marina View
Singapore 018961

+65 8323 7855
singapore@accesspartnership.com

Jakarta

Revenue Tower 21st Floor
Unit 104 SCBD Lot 13, Jl. Jend. Sudirman
Kav. 52-53
Provinsi DKI Jakarta, 12190
Jakarta, Indonesia

+62 21 5020 0949

Kuala Lumpur

Common Ground Q Sentral
Level 39, Unit 39-02 (East Wing), 2A,
Jalan Stesen Sentral 2, Kuala Lumpur
Sentral, 50470
Kuala Lumpur, Malaysia

Bangkok

188 Spring Tower
11th Floor, Unit 106, Phayathai Road
Thung Phayathai, Ratchathewi,
10400Bangkok, Thailand

+ 66 (2)-8216148

Hanoi

19th floor, Tower 1
Capital Place Building
No 29 Lieu Giai Street
Ngoc Khanh Ward, Ba Dinh Diítrict
Hanoi, Vietnam

Manila

CG8ROCKWELL Level 21, 8 Rockwell,
Hidalgo Dr., Rockwell Center, Bgy.
Poblacion, 1210
Makati City, Metro Manila
Philippines

Middle East and Africa

Abu Dhabi

Al Wahda City Tower, 20th Floor
Hazaa Bin Zayed The First Street
PO Box 127432
Abu Dhabi, UAE

abudhabi@accesspartnership.com

Johannesburg

119 Witch-Hazel Avenue
Highveld Technopark
Johannesburg
Gauteng, South Africa