BEYOND 4.0

UNDERSTANDING FUTURE SKILLS: REQUIREMENTS FOR BETTER DATA

WP 6, Deliverable 6.3
Report

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Clara Behrend, Mathias Cuypers (TUDO) and Sally Wright (IER) with Michael Kohlgrüber and Adrian Götting (TUDO)

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Author/s:	**Clara Behrend**, **Mathias Cuypers** (TUDO), **Sally Wright** (IER), **Michael Kohlgrüber**, **Adrian Götting** (TUDO)
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Deliverable 6.3 focuses on data necessary for a comprehensive analysis of skills for digitalisation. Reliable data is needed to make appropriate decisions for the New Skills Agenda for Europe, national initiatives, and VET systems. Qualitative assessments of Tasks 6.1 to 6.4 are contrasted with quantitative WP3 data to identify gaps in data, indicators and measures that support monitoring of skill requirements. The main outcome is that there are still gaps in European data on skills that leave stakeholders partially blindfolded when looking at changes in skill demand and resulting needs for adaptations of skill supply. The report formulates requirements for the improvement of data.

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BEYOND4.0 Partners

Technische Universität Dortmund, Sozialforschungsstelle Dortmund (sfs) (TUDO), Germany
Institute for Employment Research (IER), University of Warwick, UK

www.beyond4-0.eu

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List of abbreviations

AI – Artificial intelligence

AES - Adult Education Survey

ALL - Adult Literacy and Lifeskills Survey

API – Application Programming Interface

Cedefop – European Centre for the Development of Vocational Training

CVET – Continuing Vocational Education and Training

CVTS - Continuing Vocational Training Survey

DESI – Digital Economy and Society Index (DESI)

ECHPS - European Community Household Panel

EACEA - European Education and Culture Executive Agency

EC – European Commission

ECHP – European Community Household Panel

ECS – European Company Surveys

Eurofound – European Foundation for Living and Working Conditions

EQF – European Qualifications Framework

ESCO – European Skills, Competences, Qualifications and Occupations

ESJS – European Skills and Jobs Survey

EU – European Union

EU-LFS – European Labour Force Survey

EU-SILC – European Statistics on Income and Living Conditions

ETF – European Training Foundation

Eurostat – European Statistical Office

EWCS – European Working Conditions Surveys

IALS - International Adult Literacy Survey

ICT – Information and Communications Technology

ILO – International Labour Organisation

ISCED – International Standard Classification of Education

IT – Information Technology

IVET – Initial Vocational Education and Training

MTSS – Manpower Talent Shortage Survey

NACE – Statistical Classification of Economic Activities in the European Community

NQF – National Qualifications Framework

NUTS – Nomenclature of Territorial Units for Statistics

OECD – Organisation for Economic Co-operation and Development

OJAs – Online job advertisements

PES – productive, expandable and social (concept of skills)

PIAAC – Programme for the International Assessment of Adult Competencies

STEP - Skills Towards Employability and Productivity

VET – Vocational Education and Training

WEF – World Economic Forum

WP – Work Package

Executive Summary

This report, Deliverable 6.3, focuses on data necessary for comprehensive analysis of future skills for future workplaces in the context of digitalisation and Industry 4.0. The aim of this deliverable is to outline an approach to better data for the New Skills Agenda for Europe, national initiatives and VET systems. It is addressed to data producers such as European data agencies and interested researchers investigating the subject of skills alike, but also gives some indication to European policymakers about how to mitigate current gaps in data and barriers to full usage of data existing through fostering better data collection, use and presentation.

Reliable data is needed to enable stakeholders to make appropriate decisions for the New Skills Agenda for Europe. The report builds on qualitative assessments of Tasks 6.1 to 6.4 which are contrasted with quantitative data identified by WP3 and additional European data sources on skills. It looks at data, indicators and measures that support monitoring of skill requirements for digital transformation. It identifies gaps in these data that leave stakeholders partially blindfolded when looking at changes in skill demand and resulting needs for adaptations of skill supply. The report formulates requirements for the improvement of data and gives recommendations for data producers and policymakers.

The digital transformation of the economy is a challenge for many European societies. Thereby, it concerns not only the productivity of companies but also the interest of workers for (good) employment, especially those at risk of digital exclusion. Work undertaken in WP6 has established that focusing on the skill requirements for workers, as well as skill supply, is a useful way of identifying both, the gaps in current policy thinking as well as recommendations for future skill-related policies that facilitate digital inclusion and the digital transformation.

For the BEYOND 4.0 skills perspective, the focus lies thus on whether and how skill categories that represent the types of skills needed and used in a job or possessed by workers are measured and if these measures enable recent international comparisons. According to this particular perspective and the research conducted in WP3 and WP6 (drawing also on research from WP4, 5, and 8), the paper formulates several requirements for skill data which together form the yardstick against which existing data on skills are measured so that gaps in and requirements for better data are identified:

- a **distinction** should be made **between skills and related concepts**. Related concepts, such as qualifications or occupations, should not be used as a proxy for skills, if possible.
- In the comparison between job-based and task-based approaches in the debate on skill change, we consider **task-based approaches** to be better suited to reflect a dynamic understanding of job profiles.
- In order to also understand the reasons for skill changes, **other aspects** are relevant, e.g., technological change and work organisation

- Skills can be distinguished according to their **content**, which is why it is meaningful to have such a distinction between **several skill categories**, similar to the BEYOND 4.0. categorisation
- **Interacting skills**, so digital skills in combination with other skills categories needed to do a specific task, need to be measured.
- As meeting skills needs is a collaborative task of **different actors**, all perspectives need to be understood and reflected in according to data (employers, workers, educational side)
- This can be related to the **skill matching perspective**. Data on both skill needs and skill supply of the actors should be collected. While doing so, a distinction between the various types of skill mismatches must be considered and data on all of them are relevant.
- The **disaggregation of data on skill gaps and skill supply for groups at risk of exclusion** (education level, age, gender, recent migration from another country, disability) of the labour market should be possible.
- For the European skills intelligence to be useful, **harmonised data for all European member states** should be available.

A variety of data on skills is collected at a number of policy levels: at the European Union (EU) and international, national, sectoral and regional levels. This report looks at what information about skill is currently being collected on the European level, what data is needed, and what means are available to respond to and meet already existing and future skill needs from both the skill demand and supply sides.

The report looks at data that allow for international comparison between European countries. As changes due to digital transformation are in focus, datasets should allow for the analysis of change over time. The report lists measures of European surveys that capture skill shortages, skill mismatch, skill gaps and skill use or skill need in the workplace. Surveys included in the review, of which data on skills already exist, were the ESJS, PIAAC, EWCS, EU-LFS, ECS, MTSS, CVTS, AES and the Opinion survey on VET in Europe. Further datasets that were considered but rendered out of scope for this assessment were EU-SILC (which covers most of the topics formerly addressed by the ECHPS), IALS, ALL, CHEERS, REFLEX, HEGESCO, EUROGRADUATE, EBS, and the Worldbank's STEP[1]. **On this basis of existing data on skills, we concluded that while skill proxies such as occupations and qualifications supply and demand on the labour market are measured and accessible for stakeholders, data on skill categories needed for jobs and used in the workplace as well as skills taught in education are missing and hardly measured**. This leads

[1] They are not assessed in detail because they did not fulfil the minimum criteria of at least one measurement of types of skills, data available not older than 2011, and at least 5 EU countries in the sample.

to policymakers and other stakeholders needing to act partially blindfolded when taking decisions on skill strategies, education and training.

The report contrasted the requirements for skill data drawn from tasks 6.1-6.4, as presented above, with the assessed existing data on skills in European surveys and other types of data. On this basis, several requirements for better data are proposed:

- Data producers need to consider the purpose of what the data is going to be used for and by whom. To this end, all relevant stakeholders must be included in designing data collection on skills
- European data agencies should provide or at least map more fine-grained data at the sector and regional levels.
- Quantitative and other types of data that allow for within company insights should be collected by European data producers: ideally, employers and employees from the same companies need to be asked questions within one survey, so that company strategies can be directly linked to changes in jobs of employees in the companies.
- non-survey data on skills should be mapped and/or collected in a centralised way by European skill data agencies, such as the EACEA or Cedefop
- European data agencies need to ensure that for each perspective and topic (e.g. skill shortages, skill gaps, skill demand and skill supply), there are data available at an adequately disaggregated level in European quantitative surveys that facilitates unit of analyses at the country, regional, sectoral, company levels.
- Data producers, such as national and European statistical agencies, should improve the facilitation of linking existing datasets through improved coordination and harmonisation at the European level. One important use is the linking of employer surveys with employee or labour-force surveys.
- The linking of information on the skill needs of employers and/or employees with data on the supply side of skills, such as qualification contents, skills assessment surveys and graduate surveys is the other important use of linked datasets that will allow for better comparison of skill needs and skill supply.
- Furthermore, it is worth considering expansion on the sample sizes of EU surveys, especially employer surveys, to allow for better analysis while maintaining data protection and statistical validity when linking datasets. Here, policymakers and data producers on national and European level need to work together to find a viable solution.
- European data agencies should look to make as much detail as possible in datasets publicly available to stakeholders (bearing in mind data protection regulations).

- a more flexible solution to data protection in datasets, where researchers can choose the trade-off of data detail, maintaining data privacy while gaining a level of detail for the specific research topic, would be of great advantage.
- Data producers need to align measurements between surveys better to enable the comparison of measurements of the same subject between countries and EU-wide
- Data producers need to clearly and define the skills and skill concepts measured and differentiate between tasks, skills, and related measures such as qualifications and occupations.
- The standardisation of skill categories comparable to other international standardisations and a continuous measurement of skill needs and skill supply using this categorisation is needed. Data producers and policymakers need to agree on a standardisation for skill categories.
- The best validity of data measuring the skills of workers involves the direct assessment of skills. Surveys using this method, such as the PIAAC survey need to be further funded and elaborated for more skill categories.
- more timely data is required: one potential solution to collecting more timely data on skills could involve the inclusion of questions on skills needed in jobs and on current skills of workers into surveys that are conducted more frequently, such as the EU-LFS or the EWCS and the ECS.
- The measurement of interacting skills from different categories needed to do one task in combination, is needed. It is not yet possible to identify interacting of skills with existing data except for the problem-solving skills in technology-rich environments testing of the PIAAC. Data producers could for example add questions to surveys that ask about specific combinations of skills needed within jobs or ask which tasks respondents have and which skill categories they need to do them.
- Data on skills for an inclusive future are needed: Policymakers need to support according processes and data producers need to include according questions into skill surveys (most include the measurement of educational attainment, age, and gender while immigration status and work-relevant disabilities and chronic illnesses are not asked for.)
- The presentation, dissemination and accessibility of data should be tailored to suit the needs of the different key stakeholders. Good examples are the Skills Intelligence Platform and Europass.

1. Introduction

BEYOND 4.0 supports the delivery of an inclusive future of decent work and decent lives for European Union (EU) citizens. This report focuses on data requirements necessary for comprehensive analyses of skills demand and skill supply in the context of digitalisation. The aim of this deliverable is to outline an approach to better data for the New Skills Agenda for Europe, national initiatives and VET systems. It addresses data producers such as European data agencies and interested researchers investigating the subject of skills alike, but also gives some indication to European policymakers about how to mitigate current gaps in data and barriers to full usage of existing data through fostering better data collection, use and presentation.

The paper provides an assessment of existing data on skill imbalances in Europe, with a particular focus on data on skill requirement changes within jobs. It asks whether current data allow for an understanding of changes of skill use and skill requirements in workplaces over time and specifically in the context of the digital transformation, and also whether the data allow for appropriate response by the VET systems and policymakers. The demand and supply sides to skills are considered.

The report is based on assessing how existing data, measures and indicators collected at the European level fulfil the requirements derived from the research conducted in BEYOND 4.0's WP 6 tasks 6.1 to 6.4. We take the framework developed in BEYOND 4.0 deliverable 6.1 as a starting point. It defines skills as different from tasks, occupations or qualifications and thus allows for the identification of existing and missing data on skill categories and changes within occupations and jobs. For the identification of requirements for data on skills we also selectively draw on results from interviews, surveys and workshops conducted in twelve regional ecosystems, conducted as part of the WP 4 and 8 of the BEYOND 4.0 project. The requirements will be presented in section 3 in detail.

These requirements are then contrasted with existing data on skill needs, skill use in jobs and skill imbalances from surveys, job advertisement analysis and other types of data collection. The paper identifies gaps in data collection and data preparation and formulates requirements for *better* data on skills.

Furthermore, the report is complementary to the BEYOND 4.0 policy brief on *Data deficits in the digital age and how to fix the problem* (Greenan & Napolitano, 2022a) that presents insights from WP3 and 5 of the BEYOND 4.0 project. While the policy brief produced by Greenan and Napolitano (2022a) focuses on statistics necessary for comprehensive analyses of the socio-economic outcomes of the digital transformation in the EU, this report focuses more specifically on requirements for data on *skills for the digital transformation* in the EU and discusses not only survey data but also other types of European skills data. Most of the challenges and opportunities identified in the former policy brief also hold true for data requirements on skills, but there are several specific requirements for data collection on skills that will be discussed in this paper.

After this introduction, the report is comprised of four sections. The report's second section outlines why the delivery of skills information is important for several stakeholders in general and specifically for European data producers, researchers and policymakers. The third section of the report sets out how this work package in the BEYOND 4.0 project conceptualises skills and what data and indicators would be required so that appropriate decisions for the New Skills Agenda for Europe can be addressed. This includes setting out the definition for skills in WP6, and outlining which skills are relevant for the digital transformation, who the relevant actors are, and what skill categories and skill imbalances should be covered by data. Additionally, it will be asked what data is needed to link skills demand with skills supply to make it possible to identify skills gaps? The fourth section of the report provides an overview of what data and surveys are already being collected to measure skills, and an assessment is then made on whether these data are adequate to fulfil skills intelligence requirements outlined in the previous section. The final (fifth) section of the report sets out several requirements for better data and gives recommendations to data producers and policymakers.

2. Why delivery of skills information is essential

The overall objective of BEYOND 4.0 work package 6 is to achieve an understanding of the new and increasingly important skills needed for future workplaces in the context of digitalisation and Industry 4.0. Within the work package a new framework to classify new skills for the digital transformation was developed. For this a focus on within-job changes of skill demand and according needs for the adaptation of skill supply were investigated. The focus of this section lies on how the work and the perspective of WP6 relates to skills intelligence and the *New Skills Agenda for Europe*.

2.1 The importance of skills intelligence

The need for regular, coherent and systematic skill forecasts is well established (for example, see Cedefop, 2017b; Cedefop, 2018; Dickerson & Wilson, 2017; Dunkerly et al., 2022; Wilson, 2013). The ability to systematically assess and anticipate skill needs plays a fundamental role in providing a broad understanding of **the type of jobs that will be needed and what education and training will be required to deliver the right mix of skills**.

The need for better skills matching is highly important, as skills have been identified as the most important bottleneck for digitalisation (World Economic Forum, 2018, 2020). For example, in a company survey conducted by the WEF, over half (55%) of companies identified “skill gaps in the local labour market” as the main barrier to digitalisation. In contrast, just around one-third of companies (32%) saw a “shortage of investment capital” as a barrier (World Economic Forum, 2020, p. 35).

As further evidence of the importance of skills for digitalisation, the European Commission synthesises the need for digital skills in its Digital Education Action Plan, concluding that 90% of jobs will or already do require digital skills while 34% of workers are currently lacking sufficient digital skills (European Commission, 2020a, p. 13). These examples illustrate that data on skills can reveal major shortcomings which in turn can enable all relevant stakeholders to make the right decisions about investing in skills development for the future. The results of such a favourable use of data is termed ‘skills intelligence’ in the discussion (see Cedefop, 2019a).

The right skills intelligence should be available to all relevant stakeholders. From the perspective of **individuals**, it is important to develop the right skills to cope with changing demands of job tasks in a digitalised working environment. To leave nobody behind, it is important that employees and job-seekers alike have the right skills necessary to get and then keep (and do) a job. In addition, it is also important to understand these requirements for actors on the supply side, including **vocational education and training (VET) systems**, **higher education providers (HE), companies, and training providers**. The endeavour of gathering skills intelligence is a forward-looking activity focused on ‘providing guidance, preparedness and flexibility, and supporting more effective operation of labour markets’ (International Labour Office, 2015, p. 3). It also provides the foundations for assessing the potential effects of unforeseen and foreseen disruptions. This skills intelligence can also be used as the starting point for more speculative, longer horizon scanning (Dickerson & Wilson, 2017, p. 2).

To anticipate skill gaps and to make decisions about how to mitigate these gaps, reliable and meaningful data on skills are required. This includes **qualitative and quantitative data** on demand- and supply-side requirements to facilitate better **skill matching** (vocational education and training, s. D6.1, 1st report; Kohlgrüber, Behrend, Götting et al., 2020).

2.2 The New Skills Agenda for Europe

The promotion of skills intelligence was also taken up as one of the actions in the European New Skills Agenda (European Commission, 2016). The European Skills Agenda, a five-year plan, was developed to help individuals and businesses develop more and better skills and to put them to use by strengthening sustainable competitiveness (as set out in the European Green Deal, European Commission, n. y.b), ensuring social fairness (by putting into practice the first principle of the European Pillar of Social Rights in terms of access to education, training and lifelong learning), and building resilience to react to crises (based on lessons learned during the COVID-19 pandemic).

Consequently, **strengthening skills intelligence has become one of the actions in the European New Skills Agenda**, which rests on the premise that skills "are a pathway to employability and prosperity, and a vehicle for innovation" (European Training Foundation, n. y.). Relevantly, the European Commission observes that "policymakers and education providers need sound evidence of the skills which will be required in the future to help them make the right decisions on policies and reforms, education curricula and investment". So, the response of vocational education and training (VET) systems to the needs of the labour market and individuals are dependent on the right data (European Training Foundation, n. y.).

In the official communication of the European Commission on the Skills Agenda, it has more concretely been stated that skills intelligence "often […] comes too late to inform choices" (European Commission, 2020b, p. 8). A few data sources - Graduate tracking surveys, administrative data matching, artificial intelligence and big data analysis – are mentioned as having great potential (European Commission, 2020b, p. 8). However, the communication goes not further into detail and objectives are set with regard to actual skills and learning improvements of adults, not with regard to the improvement of data sources (European Commission, 2020b, p. 19).

But, one key action of the New Skills agenda are the sector skill alliances. Their establishment is funded in the ERASMUS+ programmes and they are required to collect data on skill gaps in the sectors (European Commission, n. y.a).

3. Conceptualising skills and skills data requirements

To evaluate the skills intelligence that is developed in Europe, we need a criterion to assess whether what is collected and measured is adequate. Laying the data collection against what we think is needed, shows which data gaps exists. This section explains the framework developed in BEYOND 4.0 WP 6 for understanding skills. First, the definition of skills adopted in the BEYOND 4.0 project is outlined. This is followed by a discussion about the content of skills relevant to digital transformation. Next, the relevant actors and perspectives regarding the skills that should be covered are given consideration. Finally, issues around skills matching are discussed in terms of what is needed to identify skill/s gaps in European data collection.

3.1 Defining skills in distinction to related concepts

To identify requirements for better data on skills, it is first necessary to define how skill is conceptualised for this paper, including how skills need to be distinguished from similar concepts, such as tasks, qualifications, and education levels (Behrend et al., 2022; Warhurst et al., 2019). In particular, in much of the current research, qualifications and skills tend to be conflated, even treated as synonymous (Cedefop, 2018). In addition, an important distinction needs to be made between the skills debate and more general debates about the labour market and employment per se.

Being broadly and variously defined, skills consequently lack common measurement internationally (Cedefop, 2018). In the absence of definitional consensus, what gets counted as a skill is that which can be measured (Warhurst et al., 2019). In this sense, data that is best suited to reflect the need for and supply of skills is not currently being collected. Rather, a skill is understood as something that can be measured, often via a proxy, relying on existing data collection methods. Opposite in approach, the BEYOND 4.0 research started with a definition of skill which is related to tasks, jobs and occupations but also distinguishable from these concepts.

Within the scope of BEYOND 4.0, the definition of the European Commission's ESCO classification of skills, qualifications and occupations was followed. Therein, ***occupations*** are described as a grouping of jobs involving similar content in terms of tasks and required skills. Skills are needed to perform a task. On the other hand, a ***job*** is described as a set of tasks and duties executed by a singular person (cf. Kohlgrüber et al., 2021). A ***task*** is a unit of work activity that produces output (Autor, 2013). All paid (and unpaid) work comprises a bundle of tasks: physical, intellectual and social (Fernández-Macías et al., 2016). The balance of these tasks can vary by job, but each of these tasks is underpinned by skills and knowledge. Whilst skill and knowledge can be conceptually separated, in practice, they can be hard to disentangle, particularly if the exercise of skill requires knowledgeable practice (Thompson, 1989).[2]

While there is no consensus about the meaning of the concept of skill in literature (Green, 2011), the BEYOND 4.0 concepts paper (D2.1, Warhurst et al., 2019) conceives ***skills*** as objective requirements demanded by tasks, where task compositions between jobs may vary and thus require different levels of skill. The concepts paper also points out that skills are often designated as domain-general ('generic') or domain-specific, where the former skills are transversal across occupations and the latter confined to particular occupations (i.e. job-specific). Green (2011) suggests that skills have three key features: they are productive (i.e. using a skill is productive of value), expandable (i.e. can be enhanced by training and development) and social (skills are socially determined). This approach, known as Green's PES concept of skill, has been adopted in this report (see D6.1, Behrend et al., 2022).

In practice and when conducting qualitative research in the BEYOND 4.0 project, however, the distinction between skills and qualifications poses a challenge. For example, in a Finnish ecosystem, one interviewee explicitly states that employees and jobseekers had difficulty describing their skills. Instead of identifying their skills, they provide details about their educational qualifications, i.e. degrees and diplomas, and the same was true for employers (D6.1, Behrend et al., 2022). Similarly, this type of conflation of skills and qualifications leads to surveys delivering data on qualifications, yet rarely on concrete tasks and skills. This is a major challenge that could be overcome by collecting better (as opposed to more) data. Again, this raises further dilemmas, such as how to measure specific skills in a narrow sense. Is it, for example, only possible to collect detailed information about skills from tests such as those used in the PIAAC survey? Or are proxy measures for skills still needed? These questions are among those we attempt to address in this report.

3.2 Debates on skill changes and their causes

Various strands of literature have also contributed to the debate on skill changes and their causes. Report D6.1 considers a variety of concepts, theories and labour market phenomena that are useful for these topics.[3] Thereby, the difference between the job-based and the task-based approaches is of great importance when analysing future skill requirements. As the name suggests, the job-based approach uses jobs as the unit of analysis. In this way, employment shifts can be described quantitatively, and it can be determined how many jobs have been lost

[2] Warhurst et al. (2017a) mention additional issues when it comes to the definition of skills. Accordingly, understanding of skill is dynamic, changing over time and spatially-specific. In some countries, 'skill' still refers to having and being able to apply accredited vocational knowledge acquired through a mixture of formal and on-the-job learning. In other countries it now means whatever employers want it to mean (Lafer (2004); Warhurst et al. (2017))

[3] For a detailed debate see Kohlgrüber, Behrend, Götting et al. (2020), Behrend et al. (2022) & Kohlgrüber et al. (2021)

and how many have been created due to technological change. At the same time, the approach helps to qualitatively determine which jobs disappear and/or are created (cf. Eurofound, 2015, p. 8). However, the skill categorisation of BEYOND 4.0 is much more closely related to the task-based approach. Here, the focus is on the tasks that workers perform within jobs (cf. Arntz et al., 2016, p. 12). The task-based approach assumes that jobs are not static and unreplenishable but are constantly changing. Therefore, when trying to identify which skill demands arise from digitalisation, it is crucial to rather focus on tasks than jobs, as ultimately, skills underpin tasks. The questions of relevance are how tasks change, which tasks are eliminated by digitalisation, which new tasks arise, and which concrete skills are needed to carry out these tasks (cf. Kohlgrüber et al., 2021, p. 15).

In this context, Fernández Macías and Bisello (2016) also note that the analysis of skill change must also take into account that it is not only technique-deterministic factors that are decisive. Ultimately, technological change is embedded in complex social structures. Thus, jobs should not only be considered as a bundle of tasks but must also be understood in an organisational context. Considering social factors, such as the orientation of production or service provision, are therefore fundamental to understanding the impact of technological change on work (cf. Kohlgrüber et al., 2021, p. 16). Fernández Macías and Bisello (2016) emphasise the connection between the question of 'what people do at work' and 'how people do their work' and argue for a link between work content and organisational context (cf. Kohlgrüber et al., 2021, p. 16).

3.3 Skill content relevant for the digital transformation

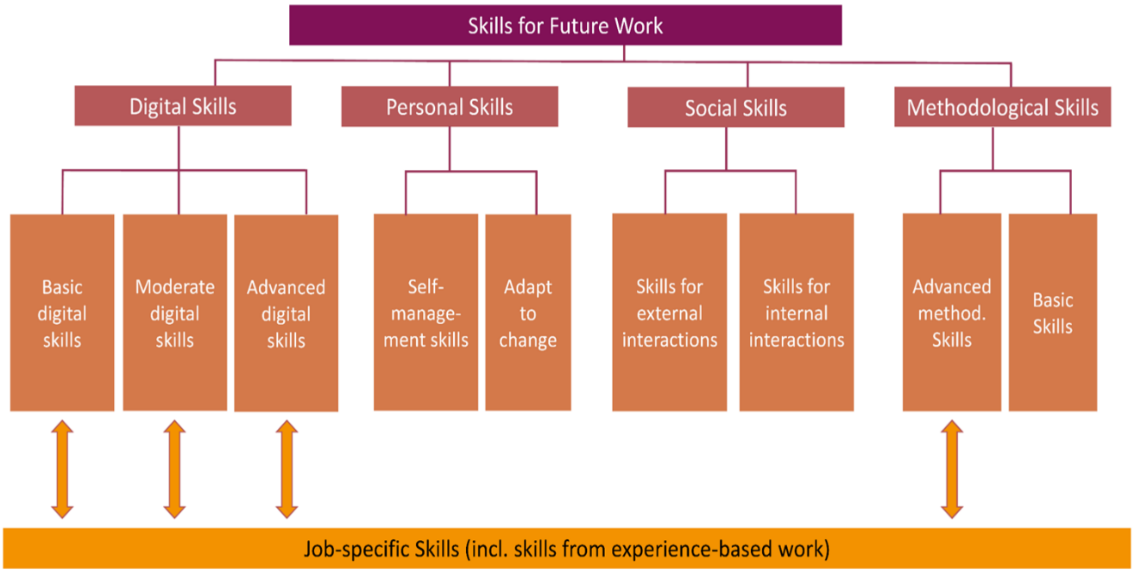
Skill requirements in terms of contents of skills were identified with the skill categorisation scheme presented in D6.1 as a basis (Kohlgrüber et al., 2021) including digital and non-digital skills (personal, social, and methodological skills), and job-specific skills. These are the skills that are relevant to digital transformation. Combining job-specific or non-digital skills with digital skills (interacting skills) plays a particular role in successful digitalisation processes (Behrend et al., 2022).

Categorising types of skills

Based on a comprehensive systematic review of the literature and validation derived from qualitative research conducted in BEYOND 4.0 work packages 4 and 8, a new categorisation was developed, as reported in the three-staged Deliverable 6.1 (see Behrend et al., 2022; Kohlgrüber et al., 2021; Kohlgrüber, Behrend, Cuypers et al., 2020). These categories were generated from findings from a systematic literature review on future skills for the digital transformation and BEYOND 4.0 project data (obtained from interviews, surveys and workshops conducted with workers, employers, and regional stakeholders in six European countries). It was found that jobs requiring more intensive digital skills also require a range of digital-complementary skills to perform new tasks associated with ICT usage. Those are for example job-specific skills (such as domain-specific understanding of the respective field of activity), a solid level of information-processing skills (e.g. literacy and numeracy), as well as the ability to communicate, collaborate and share information, give presentations, provide advice, work autonomously, manage, and influence (social skills).

As set out in Figure 1 below, this framework serves as a structuring element for empirical results on skills and, thus, a structuring element for data requirements on skills. It makes a distinction between five skill categories: four categories of transversal skills (digital, personal, social and methodological skills) and the category of job-specific skills, which continues to play a major role in the context of the digital transformation (see D6.1 3rd report, Behrend et al., 2022).[4]

Figure 1: The BEYOND4.0 full classification of skills for future work.



In the systematic review of the literature, a broad consensus emerged among the studies that were examined where increasing demand for digital skills is expected due to the increasing diffusion of digital technologies, including artificial intelligence (AI) and machine learning. Not surprisingly, all reviewed studies predict an increasing demand for **digital skills**. However, they differ on whether basic or advanced digital skills will be those most in demand in the future. Apart from this distinction of digital skills, the ESJ Survey (Cedefop, 2016) introduces another sub-category of digital skills - moderate digital skills, which entail such skills as word-processing or creating documents and spreadsheets (D6.1 1st report, Kohlgrüber et al. 2019).

Also, ***personal skill*** is a category often mentioned by experts in sector-related skills alliances and in the empirical field work of WP4 and 8. Personal skills include self-reflection, learning skills,

[4] The process of identifying these skill categories is extensively described in the second report of D6.1.

integrity, responsibility, attitude (individual values/ethics), motivation, and entrepreneurial skills such as readiness to take the initiative and risks. While some surveys consider self-reflection, integrity and motivation to learn rather as personal traits, adaptability/adapt to change, flexibility, the attitude to be open for new things, and continuous learning have been identified to be increasingly in demand in the considered studies (D6.1 2nd report, Kohlgrüber et al., 2021). Despite the ambiguous categorisation, personal skills are likely to continue to play an important role in the work of the future, as evidence from the sectoral level and company level shows (D6.1 2nd report, Kohlgrüber et al., 2021).

Social skills cover all skills related to interpersonal action. They include basic communication skills such as the exchange of information and mean more complex social interactions such as team-work and collaboration, intercultural skills, coordinating social networks, conflict resolution, teaching, mediating, negotiating and persuasion, and knowing how to be polite and friendly. Social skills are highly relevant in the context of digital transformation (here, digitalisation is understood as the increasing use of AI/automation on one hand and organisational changes on the other (see WP3, Milestone 4)). Bughin et al. (2018) and Cedefop (2018) expect an increasing demand for social skills as they are hard to automate from a technological perspective (D6.1 2nd report, Kohlgrüber et al., 2021).

Advanced ***methodological skills*** are needed to find strategic solutions on how to achieve a defined objective. For this systematic approach, problems have to be analysed and understood; then, creative solutions must be found and prioritized. Therefore, methodological skills are needed, such as problem-solving skills, creative and analytical thinking, critical thinking, and decision-making. Additionally, basic skills such as numeracy and literacy are another sub-category of methodological skills that have been analysed by the Survey of Adult Skills being part of the PIAAC programme and form the basis of the acquisition of more advanced methodological and other skills (D6.1 2nd report, Kohlgrüber et al., 2021).

Job-specific skills refer to those particular and specific skills to the field of work, domain or occupation in question. In the empirical work conducted in BEYOND 4.0 various interview partners stressed the importance of job-specific skills and work experience for the business in general but also specifically processes of digitalisation (Behrend et al., 2022). One important finding of our literature review is that advanced digital skills go along with job-specific skills in some sectors and, therefore, cannot clearly be separated from them. Particularly in the manufacturing sector with their specific plant-based digital industry 4.0 solutions and in the human health and social work sector with technologies explicitly developed for specific medical or professional care tasks that require professional knowledge, the intertwined digital and professional skills will become important (D6.1 2nd report, Kohlgrüber et al., 2021).

This role of job-specific skills as relevant in combination with digital skills brings us to the most important findings of the empirical evaluations on skill demands. That is, it is not only individual skill categories that are in high demand. Rather, combinations of different skill categories are often needed in the labour market, whereby these that are important in the digital transformation are primarily combinations of digital skills with another non-digital skill category, so to speak, demand for “digital skills plus X” skills. While not a term used in the existing literature, this phenomenon is referred to as ***interacting skills*** in BEYOND 4.0 D6.1. In this sense, different **combinations of the various skill categories interact in order for workers to perform individual tasks within their jobs**. Furthermore, as new digital technologies permeate a rising number of jobs and tasks, the ability to combine digital skills with job-specific skills is becoming increasingly important. In addition to digital and job-specific skills, findings from BEYOND 4.0 D6.1 provided examples from the empirical evidence highlighting the importance of other skill combinations. Namely, digital and methodological skills, digital and social skills, and digital and personal skills. The empirical research carried out in WP4 and 8 and analysed for the work of WP6 validates the value of looking at the interaction of skill categories rather than merely focusing on single categories of skill. Shifting from a siloed approach provides important additional insights about the impact of digitalisation on work.

Supply side of skills

Turning to the **skill supply side**, EU and national policies focus on **digital skills**. The Digital Education and Action Plan (European Commission, 2020a), Digital Skills and Jobs Coalition and the New Skills Agenda for Europe (European Commission, 2020b) have identified and prioritised the need for improved digital skills and have defined common guidelines and goals. The way EU member states are translating the EU policies **into national policies and innovating VET** systems towards digitalisation and innovation can be identified by a series of Cedefop country reports VET for the future of work[5].

Implementing a digital (skills) agenda, considering digitalisation as a key priority (Tividosheva, 2020), providing digital infrastructure (Westerhuis, 2020), anticipating future skill needs (Huismann, 2020) and sometimes even reforming the whole VET system (Koukku et al., 2020) are examples of national actions in response to the digital transformation. Despite these activities towards digitalisation in education and training, a clear gap between the digital skills being provided and those needed remains. For example, progress in developing digital skills between 2017 and 2019 has been modest (Koukku et al., 2020). Much is still to be done to close skill gaps, including tracking the effectiveness of skills actions and initiatives (European Union, 2020).

While there is a monitoring of national activities regarding the further development of VET systems (Cedefop, 2020a, 2020b, 2020c, 2020d, 2020e, 2020f, 2020g), there is a **lack of available quantitative data that can be used to monitor progress and to evaluate the effectiveness of programmes**. Household sample surveys asking for or assessing skills of workers can give an indication of progress if they measure skill categories detailed enough, in a timely manner and in an adequate frequency in order to pinpoint the effects of policy implementation.

In summary, current European and national policies are mainly focused on improving **digital skills**. While non-digital skills are also addressed, this is not done as systematically as is the case

[5] https://www.cedefop.europa.eu/en/country-reports/vet-future-work

for digital skills. As a result, initiatives to improve digital skills often operate in isolation. This siloed approach to improving digital skills often seems to come at the expense of other types of complementary skills development. As there is no tracking of the impact of policies in terms of the skill categories used in BEYOND4.0, it is difficult to compare the demand and supply requirements of future skills across all of the relevant digital and non-digital categories.

Better data are available for (basic/moderate and advanced) digital skill gaps, however, this is limited to relatively simple measures of basic, moderate and advanced digital skills. For example, results from Cedefop' s ESJS (2015) show a large deficit in basic and moderate digital skills in some countries (namely, Luxemburg, Malta, Lithuania, Bulgaria), moderate deficits in most other countries, while only very few countries show deficits in advanced digital skills (namely, Sweden, Poland and Finland).

Reports on the supply side (at both the EU and country levels) are focused on the way skills should be developed by the VET systems (that is, the 'how'), where pedagogical innovations (project-based learning), development of (digital) teacher skills, and filling gaps between system and classroom level are among the suggestions for improvement. **However, the issue of whether and to what extent the right skills are being taught is important for the understanding of emerging gaps in training offers.**

Particularly at the sectoral level, it has become obvious that **integrating job-specific and digital skills is highly important for digital transformation.** This implementation of innovation and digitalisation of VET in national and EU policies is a general issue of ***responsiveness*** of VET systems to changing skill requirements. While many VET programmes, initiatives, strategies and projects are already in place which aims to foster the development of digital skills and (to some extent) non-digital skills, there remains a gap between skill demand and skill supply for the digital transformation.

Although there are clear differences between the various Member States, progress in closing (digital) skill gaps are rather modest. While increased responsiveness is a common trend of national VET systems in Europe (Markowitsch & Hefler, 2019, p. 9), responsiveness and inclusiveness are directly linked with each other. This situation creates, in general, **a need to build appropriate capacity for the VET systems to become more responsive to technological changes and their impact on skill needs.**

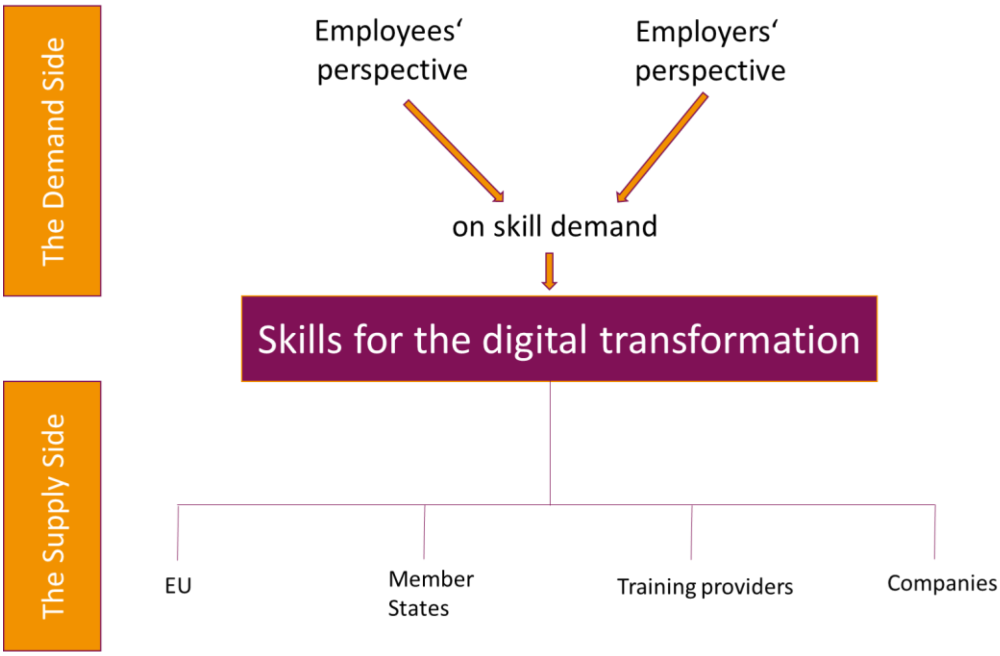
However, in the context of the COVID-19 crisis, national VET systems have been proven to advance responsiveness to this disruptive challenge (OECD, 2020). When physical access to schools and access to workplaces were restricted during lockdowns, the need for distance learning became paramount. This situation initiated a variety of measures that enabled learners to make use of digital tools. The COVID-19 crisis offered opportunities **for VET systems to track how they respond to this disruptive change and evaluate which measures prove to be particularly effective**. To date, there is no effective ***tracking*** of all the policies and programmes that aim to close skill gaps. As a result, a number of initiatives and measures are launched without being able to systematically assess their effectiveness.

3.4 Skill matching and relevant actors

When it comes to what data on skills should be collected, it is also necessary to consider the perspectives of relevant actors. That is, who should data be collected from, such as companies, employees and/or VET and HE/FE providers? A good starting point to bring these actors together is by focusing on skills matching, i.e., skill demand and supply. **To make informed decisions based on better data, matching skill demand and skill supply is needed to identify and mitigate skill mismatches.**

The concept of skill mismatch also requires an understanding of both the skills possessed by workers and the skills needed in work (D2.1, Warhurst et al., 2019). Here, Green's (2013) framework of "skill formation and the deployment of skilled labour" provides a helpful starting point for integrating both sides. Green identifies two markets for skills. On the one hand, there is a market for skills supply, in which different actors provide learning and training. On the other hand, a market for skills demand exists. On the demand side, the requirements of employers and employees have to be estimated. On the supply side, the consequences for different education and training actors (at EU, national, sectoral, regional and company levels) have to be estimated to fulfil the employers´ and employees´ current and future skills requirements. Figure 2 below represents the general framework of skills demand and supply covering the different groups of actors.

Figure 2: General framework for skills demand and supply



The issue of skills mismatch is a common concern to policymakers, employers and workers alike. However, the concept of skills mismatch is often not well understood (Green, 2016; Payne, 2017). The OECD (2016b) defines a skill mismatch as the suboptimal allocation of workers to jobs resulting in over or under-qualification. This definition uses qualifications as the proxy of skills and measures skill mismatch at the level of the employee (cited in D2.1, Warhurst et al., 2019).

Palmer (2017, p. 8) defines skills mismatch as the lack of matching between the skills that are available in (or supplied to) the labour market and the skills that are in demand in the labour market. Like the term skill itself, the term skills mismatch has been used to refer to a variety of situations (Comyn & Strietska-Ilina, 2019; Green, 2016; Palmer, 2017). Palmer (2017) identifies three circumstances where the term 'skills mismatch´ is used, as follows:

- Where individuals are over- or under-qualified or skilled for a job (vertical mismatch);
- Where firms are not able to attract the right skills or where there is a genuine lack of adequately skilled people (skills gaps, skills shortages); and
- Where individuals have skills that have become obsolete (skill obsolescence).

We then add the skill mismatch where individuals do not have (all) the right skill categories that are needed for a job (skill gap, horizontal mismatch).

Along similar lines, Comyn and StrietskaIlina (p. 2) note that skills mismatch has been used to describe over-qualification (over-education), under-qualification (under-education), over-skilling, under-skilling, skill shortages, the field of study mismatch and skill obsolescence.

A short description of each type of skills mismatch is set out in Table 1 below. While from Figure 3 it is shown that mismatches can occur for organisations in both internal and external labour markets. The first is called a skills gap and refers to a situation in which an employer believes that existing employees do not possess the skills to perform their tasks successfully or the employees report that their skills do not match the perceived skill requirement of their jobs. The second is called a skills shortage and refers to aggregate supply in the labour market not meeting demand and is manifest for employers in recruitment problems due to a lack of suitably qualified candidates (McGuinness et al., 2018; cited in D2.1, Warhurst et al., 2019, pp. 34–35).

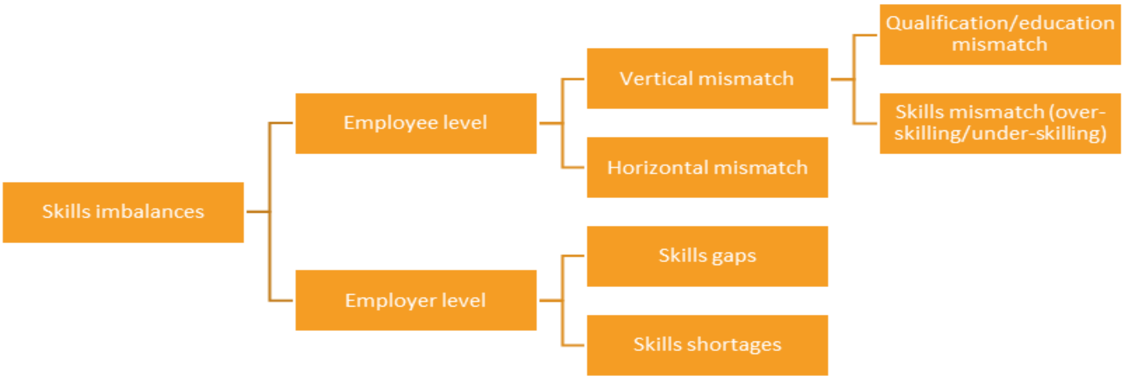
Table 1: Types of Skills Mismatch description

Skill shortage	Demand for a particular type of skill exceeds the supply of people with that skill
Skill surplus	Supply for a particular type of skill exceeds the demand of people with that skill
Skill gap	The type or level of skills is different from that required to perform the job adequately
Horizontal mismatch (field of study)	The type/field of education or skills is inappropriate for the job

Over-skilling (under-skilling)	Workers have more (less) skills than the job requires
Over-education (under-education)	Workers have more (less) years of education than the job requires
Over-qualification (under-qualification)	Workers hold a higher (lower) qualification than the job requires

Source: Palmer (2017, p. 11)

Figure 3: The impact of skills imbalances at the employee and employee levels



Source: Warhurst et al. (2019, p. 35); based on McGuinness et al. (2018)

Crucially for policymakers, these various forms of skills mismatch are very different in how they manifest themselves, how they are measured, what causes them and how their consequences are felt. For example, some relate to mismatches experienced by employees, others to employers and firm-level difficulties such as skill underutilisation, uncompetitive wages and poor working conditions, and others to factors such as low-quality education, demographic change, rapid technological development and new forms of work organisation (Comyn & Strietska-Ilina, 2019).

This makes data on the different types of skill mismatch necessary for policymakers to take effective legislative action and tackle the actual skill mismatches.

3.5 Skills for an inclusive digital transformation

The final aspect for which good data about skills is required, is related to **social inclusion**, where a highly debated issue in the discourse on digitalisation is the threat of the so-called **'digital divide'**. There are growing fears that some groups in society will be permanently left behind in the digital labour market. In particular, people with disabilities, older people, less educated workers and immigrants are seen as such vulnerable groups exposed to exclusion from digital work.

The 'digital divide' concept is used to characterise the unintended yet detrimental consequences of digitalisation. It is argued that digitalisation is likely to widen the gap between those with digital skills and those without them. There are concerns that digitalisation will worsen gaps between those with higher educational attainments and those with lower (or no) qualifications between upper and lower socio-economic echelons. To some extent, there is emerging evidence that these fears are playing out. However, there are also examples of more positive alternative scenarios that depict a more inclusive society and a more inclusive labour market (see e.g. OECD, 2019). In order to monitor this development, data on digital skills and their distribution in the population and the labour market are needed.

One risk of exclusion stems from the fact that employees of bigger companies get more opportunities to participate in further training and more often have access to training that is tailored to recent skill needs of the company than employees in smaller firms and unemployed people. With these skills, employability improves relatively to those who do not acquire them. Employees of small and medium-sized companies and unemployed workers are at risk of missing out on skills that become more important or emerge as new skills in the digital transformation. In the qualitative research in WP4 and 8 that was analysed in D6.1 (3rd report), we observed that bigger companies had their own training departments that could flexibly adapt their trainings to emerging skill needs or they did hire training providers to offer tailored courses for their employees. The interviewed experts stated that general education systems usually take more time to adapt their education programmes than measures they can take within the company or with private training providers. This risk translates into a need for **data about emerging skill needs on the one hand and the contents of training offers, including VET programmes and Higher education programmes on the other**, so that gaps between the two can be identified and tackled by training providers and policymakers.

New digital technologies may also be used to support the inclusion of disadvantaged persons to take part in labour markets and be active in their society. This is a promising avenue for many such groups that have previously been excluded from, or marginalised in, the labour markets. This can happen for example through assisting technology, such as voice-based machine assistance in different languages for migrant workers who yet have to learn the language of their resident country, it can be the digitalisation of tasks that formerly required physical work, making access for less able-bodied people easier or the digitalised handling of complex machines with simplifying machine steering equipment that require less complex knowledge for operators.

Moreover, in previous modes of production, 'able-bodiedness' was a precondition for employment. In digital production, physical performance may not be as critical. People with certain types of physical disabilities can perform demanding ICT, expert or research tasks. This means that the concepts of 'disability' and 'able-bodied' will change and maybe gradually become obsolete in the digital mode of production. Thus, there is a potential for digitalisation to enhance inclusiveness in the labour market. For this, beyond the realm of skills, data is necessary about which technologies can enable these more inclusive ways of work, how this can be implemented and who can benefit from these technologies. From a skill data perspective, it is important to **monitor whether people who are currently considered disabled have the adequate skills** that will enable them to make use of the potential of the digitalisation. **Surveys that ask for skill categories should include questions on disability status.**

To be able to develop effective skills policies to improve (digital) inclusiveness of groups traditionally disadvantaged in the labour market or vulnerable groups, it is necessary to have good data so that future skills gaps can be tackled in an inclusive way and the impacts of digitalisation can be **disaggregated for the different groups at risk of exclusion from the labour markets**. Relevantly, education is thought to be a key factor for social inclusion and the acquisition of skills needed in the digital society and working life. Skill data should include measures that allow for monitoring of skills of people who are considered part of these groups and to also **look at specific needs for training methods, access to training or specific categories of skills that would help more people to get decent work.**

3.6 The central requirements for data on skills in the digital transformation

Summarising the previous sections, some prerequisites derived from our understanding of skills can be noted. The idea is that data should cover this understanding and the presented perspectives on skills as well as possible.

For the BEYOND 4.0 skills perspective, the focus lies on whether and how skill categories that represent the types of skills needed and used in a job or possessed by workers are measured and if these measures enable recent international comparisons. This focus is due to the theoretical and empirical understanding that digital transformation, for many, if not most jobs, changes skill demand incrementally rather than disruptively. That is, the sense that changes happen at such a pace that adaptations of task composition of jobs and smaller reorganisations between job roles are more likely than complete obsolescence of employees' jobs or skill sets (for further details see BEYOND 4.0 Deliverable 6.1 reports versions 1 and 2, Kohlgrüber et al., 2021; Kohlgrüber, Behrend, Götting et al., 2020).

Therefore, we see the following aspects as requirements for better data:

- A **distinction** should be made **between skills and related concepts**. Related concepts, such as qualifications or occupations, should not be used as a proxy for skills, if possible, and be measured on their own account.
- In the comparison between job-based and task-based approaches in the debate on skill change, we consider **task-based approaches** to be better suited to reflect a dynamic understanding of job profiles and the related changes in skill demands.

- In order to also understand the reasons for skill changes, **other aspects** are relevant and need to be measured, e.g., technological change and work organisation
- Skills can be distinguished according to their **content**, which is why it is meaningful to have a distinction between **several skill categories**, similar to the BEYOND 4.0. categorisation
- **Interacting skills**, that is digital skills in combination with other skill categories needed to do a specific task, need to be measured.
- As meeting skills needs is a collaborative task of **different actors**, all perspectives need to be understood and reflected in according to data (employers, workers, educational side)
- This can be related to the **skill matching perspective**. Data on both skill needs and skill supply of the actors should be collected. While doing so, a distinction between the various types of skill mismatches must be considered and data on all of them are relevant (see Table 1).
- The **disaggregation of data on skill gaps and skill supply of groups at risk of exclusion** of the labour market (education level, age, gender, recent migration from another country, disability) should be possible.
- For the European skills intelligence to be useful, **harmonised data for all European member states** should be available. Availability in this case also means that available data is presented in a targeted way so that it can be used by stakeholders.

4. Review of existing data

This section sets out details on what data on skills is already being collected, as well as the extent to which these data fulfil the requirements in line with the BEYOND 4.0 perspective on skills that is set out in the section above.

Based on the data requirements on skills described in section 3, we assess the adequacy of existing data measuring skill needs and skill supply. We start with looking at quantitative datasets that allow for international analysis of data within the European Union. We then look at other types of data sources as all types of data add to the richness of information on skills and contribute their own quality of insights that add up to a more detailed picture of how skills need to change in light of the digital transformation and how the supply side of skills does and can adapt to these changing skill needs.

Before we have a closer look at existing datasets, it is worth mentioning that (as several skill data overviews have found) there is data available on occupations needed in the labour market on Europe-wide, national and regional levels (Baiocco et al., 2020; Eurostat, 2016; OECD, 2017). Also, there is adequate data on the demand and supply of qualifications. Data on both have been collected by member states and supra-national statistical agencies for many years now (labour force surveys) (cf. Baiocco et al., 2020; Eurostat, 2016; OECD, 2017). These measures are used as skill proxies. This means that they do not directly measure skills in demand or skill supply but are related concepts.[6]

On the basis of the skill proxies of occupations, qualifications and educational attainment, there are also forecast exercises for Europe (Cedefop & Eurofound Skills Forecast, see also overview for EU and national forecast exercises in OECD (2016a)) that use them to predict skill demand and supply developments for Europe for different timeframes (short-term to long-term). But, these approaches neglect the changes and adaptations that happen within occupations, jobs, curricula, and education systems by design and thus are not sufficient to answer questions about skill changes of the focus of work package 6 of the BEYOND 4.0 project[7].

Accordingly, the focus of this assessment of existing data lies on the measurement of skill imbalances that occur due to the changes on the workplace level and that need to be encountered by adequate adaptations of skill supply (either by training or reorganisation within the organisation, such as job role changes).

4.1 Existing datasets measuring skills

In the following section, building upon the work of Baiocco et al. (2020) while adding some dimensions important for the BEYOND 4.0 WP6 perspective on skills in the digital transformation, the available quantitative datasets that include measures of skill topics are distinguished by the following dimensions according to the methods and research design used:

- Actors asked/group of respondents (employers, employees),
- Skill topics measured (skills shortages, skill gaps, skills possessed, current skill needs, likely future skills needs etc.),
- Measurement methods: self-reported facts, subjective/perceived, skills testing/assessment (direct)

[6] As occupations represent bundles of similar jobs with similar tasks and according skill needs, they represent a useful skill proxy when skills demand needs to be analysed on a highly aggregated level, such as national or international labour market development. Qualifications represent the certified participation and successful completion of training programmes. This indicates that people who hold these qualifications should have developed a certain set of skills as defined by the according curricula. Here, we cannot differentiate between single skills or skill categories. Also, qualifications are different between regions and countries and training programmes do change their content over time. But, qualifications are usually used to analyse skill demand and skill supply on an aggregated level, as it is one of the few skill proxies that allow for comparison of both sides.

[7] For an overview on EU and national forecasting exercises in OECD (2016a)

- Timeframe (which years, how much time between the first and last wave, how old is the last data, focus on past, present or future skills),
- Longitudinal vs cross-sectional design,
- Countries included.

Baiocco et al. (2020) present an overview of many surveys 29rganization them in most of these dimensions and also defining central types of surveys measuring skills.

Accordingly, only a summary of information relevant to the skills topics and perspective on skills is discussed below. It is important here to state that relatively few current surveys measure skills in the understanding of this paper and allow for international comparisons. Within this group, we looked in more detail at those surveys that matched the following three criteria:

- A survey needed to have at least one measurement of the skill categories needed in the workplace or the 29rganization surveyed or held by the respondent.
- Data is available for at least one wave of a survey after 2011.
- A survey needs to include at least 5 EU countries.

From the available surveys, only some match the defined criteria in terms of coverage of countries and timeliness. Those are PIAAC, ESJW, EWCS, ICT usage in households and by individuals, ECS, MTSS, the Future of Jobs Survey, AES, the CVTS and the Opinion Surveys on VET in Europe. Table 2 presents how those surveys are designed in terms of methodology and what indicators or measures are included that provide insights into skill imbalances beyond the proxy measures of occupation and educational qualifications.

Table 2: International surveys on skill imbalances

Survey	Skill concepts and skill imbalance measured	Type of measurement	Targeted groups of respondents	Countries Covered	Years covered	Longitudinal or cross-sectional
PIAAC	Categories of skills, skill mismatch, qualification mismatch and field of study mismatch (source: Baiocco et al. 2020)	Skills Assessment and subjective	Household sample	ONE CYCLE **2012**: AUS, AUT, BEL, CAN, CYP, CZE, DNK, EST, FIN, FRA, DEU, IRL, ITA, JPN, KOR, NOR, NLD, POL, RUS, SVK, ESP, SWE, UK, US; **2014**: CHL, GRC, IDN, ISR, LTU, NZL, SGP, SVN, TUR; **2016**: ECU, HUN, KAZ, MEX, PER		Cross-sectional
ESJS	Self-assessment of skill imbalances, categories of	subjective	Household sample	EU 28	2014 and 2020/2021	Cross-sectional

Survey	Skill concepts and skill imbalance measured	Type of measurement	Targeted groups of respondents	Countries Covered	Years covered	Longitudinal or cross-sectional
	skills in current job					
EWCS	tasks in daily work, skill mismatch, training participation	subjective	Household sample	**2020/21**: 37 countries: EU member states, the UK, NO, CH, AL, BA, XK, ME, MK, RS, TR **2015**: 35 countries (added BA) **2010**: 34 countries, EU members, NO, HR, MK, TR, AL, ME, XK, **2005**: 31 countries, EU members, NO, HR, TR, CH **2000-2002**: 16 countries: EU members, NO, TR and new member states in 2001 **1995-1996**: EU **1990-1991**: EU	1990 – 2021 every 5 years	Cross-sectional
ICT usage in households and by individuals	Activities at work that require digital skills and basic digital skills	subjective	Household sample	EU countries, plus OECD coverage by use of same questionnaire	Yearly since 2004	cross-sectional
ECS	Skill shortage and skill gaps, *contextual*: work 30rganization, workplace innovation, HR practices, employee participation and social dialogue (source Baiocco et al. 2020)	subjective	employers	**2019:** EU 28 **2013**: EU 28 plus Croatia, North Macedonia, Iceland, Montenegro and Turkey **2009:** EU Member States, Croatia, North Macedonia and Turkey **2004/5**: 21 countries, including the EU Member States, Cyprus, Czechia, Hungary, Latvia, Poland and Slovenia		Cross-sectional
MTSS	Employers hiring difficulties – skill gaps, skill shortages (source:	subjective	employers	43 countries: JPN, PER, HK, BRE, ROM, GRC, IND, TWN, MEX, TUR, NZL, BUL, COL, HUN, CRC, PAN, DEU, GTM, AUS,	2006 and every year	Cross-sectional

Survey	Skill concepts and skill imbalance measured	Type of measurement	Targeted groups of respondents	Countries Covered	Years covered	Longitudinal or cross-sectional
	Baiocco et al. 2020)			POL, SWI, SGP, AUT, ISR, SWE, ARG, CAN, USA, ZAF, NOR, FRA, ITA, SVK, SVN, BEL, CHN, FIN, CZE, NLD, ESP, UK, IRL		
Future of Jobs Survey	Current and future skill needs (single skills), re-skilling needs	subjective	Employers (only biggest of a country)	OECD countries	2016, 2018, 2020	Cross-sectional
AES	Self-reported language skills, participation in education and training in the last 12 months	subjective and self-reported (participation in training)	Household sample	**2007** 26 (in SUF file) countries: BE, BG, CZ, DK, DE, EE, EL, ES, FR, HR, IT, CY, LV, LT, HU, NL, AT, PL, PT, RO, SI, SK, FI, SE, UK and NO; **2011** 30 countries: BE, BG, CZ, DK, DE, EE, IE, EL, ES, FR, IT, CY, LV, LT, LU, HU, MT, NL, AT, PL, PT, RO, SI, SK, FI, SE, UK, NO, CH and RS and **2016** 33 countries: Addition of HR, MK, BA.	2007, 2011, 2016	Cross-sectional
CVTS	skills taught in vocational education	subjective	Employers (over 10 employees)	EU countries	1993, 1999, 2005, 2010, 2015, 2020	Cross-sectional
Opinion survey on VET in Europe	Skills taught in vocational education, skills categories	subjective	Household sample	EU countries	2016	Cross-sectional

Sources: Baiocco et al. 2020, Cedefop, 2017a; Eurofound, n. y.; Eurostat, n. y.; OECD, n. y.b

Household sample surveys

Those data that allow for **international comparison** can be divided by the actors asked to complete the surveys (that is, the respondent groups). The European Community Household

Panel Survey (ECHP)[8], the EU Statistics on Income and Living Standards (EU-SILC)[9], the Community survey on ICT usage in households and by individuals and the European Labour Force Survey (EU-LFS) are **household sample surveys** and can be 32rganizatio as **labour force surveys** that ask respondents about some aspects of skills related to employment and labour market statistics, such as occupation, educational attainment, current job, wages and household income. As no direct/non-proxy measure of skill is included, those surveys do not fulfil our requirements except the Community survey on ICT usage in households and by individuals.

There are also household sample surveys that give insight into adults' training and lifelong learning. There is Cedefop' s Opinion Survey on Vocational Education and Training in Europe[10] , which asks respondents whether they think that certain types of skills are developed in educational programmes, e.g. upper secondary education. Note that this survey is explicitly an opinion survey and does not provide information on curricula or education programmes. It asks respondents (besides their opinion and image of vocational education) whether they thought they developed certain skills in VET. While here, it is asked about the skills supply side, it is not asked about the demand side, that is, whether the respondents use certain skill categories in their current jobs.

The Adult Education Survey (AES) also includes indicators that give information about adults' participation in training and their language skills.

Assessment and testing of skills

Looking at the selected surveys in Table 2, only the Programme for the International Assessment of Adult Competencies (PIAAC)[11] survey include actual **testing or assessment of skills**, which forms another type of survey according to Baiocco et al. (2020). The strength of these types of surveys lies in directly testing the respondent's skills so that the measurement is objective. Further surveys that follow this type of skill assessment not investigated at this point are the International Adult Literacy Survey (IALS) and the Adult Literacy and Lifeskills Survey (ALL), which were however not continued. Each of these surveys directly measured skills from certain skill categories and made it possible to understand better to which degree skills were developed and could relate this indicator to questions on the perceived over- or under-skilling of these same individuals. The skills testing is costly and time-consuming and thus has not been developed for all possible types and levels of skills and is also not conducted with a high frequency.

[8] https://www.eui.eu/Research/Library/ResearchGuides/Economics/Statistics/DataPortal/ECHP

[9] https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions

[10] https://www.cedefop.europa.eu/en/networks/refernet/thematic-perspectives/opinion-survey-on-vet

[11] https://www.oecd.org/skills/piaac/

The PIAAC survey, coordinated by the OECD, currently combines data from one cycle, with data collected in three rounds that were conducted in different groups of countries (2011/12, 2014/5, 2017), so that to date, each country has only been surveyed once (except Germany which proceeded on its own account whith a longitudinal PIAAC-L survey). The OECD will begin a new cycle of PIAAC surveys in 2022 and 2023. It tested literacy, numeracy, and problem-solving in technology-rich environments skills in the first cycle[12], i.e. skills of the categories basic methodological skills and digital skills of respondents, but did not include testing on personal, social, and job-specific skills. It did include a skills use module on cognitive, interaction and social, physical and learning skills. In the second cycle the skill use module will still be the same, but the tested skills will change so that now, adaptive problem solving skills (instead of problem solving skills in technology-rich environments) will be tested, but it is still 33organisation33l in a very similar way. Two new modules will enrich the data of the second cycle of the PIAAC survey: socio-emotional skills and an employer survey on skill gaps and possibly questions on training measures, HR practices and work 33organisation[13].

Skill mismatch surveys

Another type of survey is called **skill mismatches surveys** by Baiocco et al. (2020). An example that is also included in Table 2 is the European Skills and Jobs Survey (ESJS). The ESJS measures skill by asking employees directly about their work, skills needed to perform their job, skills possessed and the mismatch between these two. The ESJS covers all the BEYOND 4.0 skill categories (digital, personal, social and methodological skills) but not the job-specific skills in their survey.

Arguably, Eurofound's European Working Conditions Survey (EWCS) can also be included in this category because the survey contains a question in which workers are asked about the perceived adequacy of their skills for their current job's tasks and duties14. The EWCS also has the advantage of including questions on the work 33organisation. The EWCS does not ask about skills or skill categories but includes questions on activities and situations at work that can be translated into tasks by researchers. These questions cover a range of tasks that would require basic digital, personal, social and methodological skills. Nonetheless, this survey has been developed to measure working conditions and is a rather indirect measurement of skill needs.

Graduate surveys

[12] For additional information, see https://www.oecd.org/skills/piaac/

[13] For additional information, see https://www.oecd.org/skills/piaac/piaacdesign/

[14] The EWCS also includes other task-related questions, e.g. on repetitiveness of tasks, increase of tasks in the last 12 months, interaction with colleagues and supervisors.

Datasets that give insights into the supply side of skills also include **graduate surveys directed at tracking the destination of higher education graduates**. Those are CHEERS, REFLEX, and HEGESCO (Baiocco et al., 2020), all of which have no waves younger than 14 years (HEGESCO has the latest data of the three, with the last wave from 2008) and included some countries of Europe but were not run in all European countries. Therefore, those surveys have not been included in Table 2. These surveys allowed for the measurement of field-of-study (mis)match and qualification (mis)match of recently-graduated workers (Baiocco et al., 2020, p. 26). Within the ERASMUS+ European Union funding scheme, the project EUROGRADUATE is currently developing a European graduate survey. The first wave of a pilot survey was conducted in eight countries of the European economic area between 2018 and 2019, and a second wave of the pilot survey will take place in 17 countries between 2022 and 2024[15]. Scientific Use Files of the data of the first wave are available to the public. In the publicly-tested survey, questions were included that allow for a skill gap analysis on the level of skill categories. Respondents are asked to what level they needed those skills in their current jobs and how their level of those skills currently are (Mühleck et al., 2020).

Employer surveys

Another type of survey are **employer surveys** that ask the employer side about their 34organisation's skill needs, perceived needs for qualifications, occupations or skill mismatches. Often, they also provide information on skill supply in terms of training of employees and perceived supply of skills in the workforce, and the perceived quality and effectiveness of education and training. Some of them also ask for 34organizationa34l characteristics such as work 34organisation or human resources (HR) practices (Baiocco et al., 2020). While Baiocco et al. (2020) also mention the European Business Survey (EBS), the European Company Survey (ECS)[16] and the Manpower Talent Shortage Survey (MTSS)[17], only the latter two are still being iterated. There is also the World Economic Forum's "Future of Jobs" report that asks very detailed information about skill needs of employers, using the taxonomy of O*Net (WEF 2020) and the Continuing Vocational Training Survey (CVTS)[18].

The only employer surveys mentioned where there is access to raw data for independent statistical analysis are the ECS and the CVTS. The ECS has been conducted every four years, starting in 2004 (formerly known as the European Establishment Survey on Working Time and Work-Life Balance) (Baiocco et al., 2020). The CVTS is conducted every five years, with the last iteration conducted in 2020. Both are included in Table 2. The employer survey CVTS covers all

[15] For further information go to https://www.eurograduate.eu/

[16] https://www.eurofound.europa.eu/surveys/european-company-surveys

[17] https://www.manpower.co.uk/staticpages/10429/talent-shortage-survey/

[18] https://ec.europa.eu/eurostat/web/microdata/continuing-vocational-training-survey#:~:text=The%20Continuing%20Vocational%20Training%20Survey%20%28CVTS%29%20is%20part,training%20in%20enterprises.%20It%20covers%20the%20following%20topics%3A

of the skill categories but not the personal skills category and also asks for technical and job-specific skills.

And then, there is one survey that combines employee and employer survey methods into one, offering unique analysis opportunities: The World Bank's "Skills Toward Employability and Productivity" (STEP) Survey. To date, however, this survey is not run in EU member states as it is tailored to collect data on skills in low- and middle-income countries (see Pierre et al., 2014).

The PIAAC survey's second cycle will include a module directed at employers, asking about "skill needs of enterprises, strategies to address skill gaps, business factors affecting demand for skills" (OECD, n. y.a).

For further details on the exact questions on skills, see Appendix C in deliverable 6.1 of the Beyond 4.0 project (Kohlgrüber et al., 2021, pp. 70–83).

4.2 Other types of European data for the analysis of future skills in the digital transformation

Beyond the method of quantitative surveys, other data sources and tools to present data and results help to have a richer picture of skills and give insights into the changing skill demands in jobs, occupations, sectors and countries.

Job advertisement analysis

In addition to surveys as well as skill assessments, another method to indirectly measure skills and especially skills demand is the analysis of labour information. For instance, one potential data source that is principally designed to mediate jobs, i.e. to bring potential employees and employers together. Baiocco et al. (2020, pp. 35–36) present a number of examples of such portals:

- Privately run portals, such as, e.g. *Indeed,* or *Monster*, that enable the filtering of job vacancies as well as an entry of own skills and qualifications for the sake of finding a job, but also portals that concentrate on brokering single tasks to employees (such as, e.g. TaskRabbit).
- Furthermore, with the Europass and the EURES job mobility portal, public offerings provided by the EU are also presented.

These labour market portals can be seen as **potential sources for Big Data analysis**. However, Baiocco et al. (2020, pp. 35–36) stress that there are several problems associated with such use, including technological, legal, ethical and methodological challenges.

However, such analyses exist. A prominent example is the **Skills-OVATE** tool (Skills – ONLINE Vacancy Analysis Tool for Europe) of CEDEFOP[19]. As described in more detail in D6.1 (Kohlgrüber et al., 2021, p. 52), the Skills-OVATE is a Big Data analysis of more than 100 million online job vacancies (Cedefop, n. d.–a). Various methods are used to collect its data - scraping, crawling, and access via API from "thousands of sources, including private job portals, public employment service portals, recruitment agencies, online newspapers and corporate websites" (Cedefop, n. d.–b). After a process of data cleaning, the **vacancies are classified according to different dimensions**, e.g. occupations, countries/regions, and demanded skills (see Cedefop, 2019b, pp. 20–27). In addition, the **skills here are categorised according to the classifications ESCO and O*NET** (Cedefop, 2022)[20].

Rentzsch and Staneva (2020, pp. 3–4) present tools that also analyse skills by the use of labour market information, but not on the basis of job vacancies: The **OECD Skills for Jobs Database** analyses skills in occupations on a 2-digit ISCO-08 level (OECD, 2017, pp. 29–31). It follows a two-step methodology: in a first step, five sub-indices (wage growth, employment growth, hours worked growth, unemployment rate and under-qualification growth) are used to measure "the extent of the labour market pressure", i.e. the degree of surpluses and shortages within single occupations. In a second step, using the **O*NET database of skills and occupations**, those occupations are then linked to the underlying skill requirements. For their analysis, the database makes, e.g. use of the EU-LFS and the EU-SILC (ibid., p. 31).

Cedefop's Skills Intelligence Website: Bringing results from different data sources together

Cedefop developed an approach to skills intelligence which presents a broad range of indicators and statistical data. It presents skills-related data to a wider public. The Skills Intelligence platform (formerly known as *Skills Panorama*) entails 57 indicators from 8 data sources[21]. Some of these data sources are gathering data on their own (e.g. European Skills and Jobs Survey (ESJS), the EU Labour Force Survey (EU-LFS), or the Skills-OVATE), whereas others evaluate data which was previously collected elsewhere (e.g. the VET Dashboard or the European Database

[19] Another tool for job vacancy analysis that however is not addressing the European market is provided by the US company Burning Glass Technologies (BGT) includes "100 million job advertisements together with over 100 million online CVs and candidate profiles" Rentzsch and Staneva (2020, p. 8). It "is used to create a taxonomy with over 30,000 skills that is updates fortnightly" (ibid.).

[20] An important contribution to the analysis of job vacancy data, as well as a prerequisite for the Skills-OVATE project, was also made within the ESSnet Big Data II project of the European Union, which ran from 2018 to 2021 Baiocco et al. (2020, p. 36); Debusschere et al. (2021). One purpose of one work package of the project was to develop "statistical estimates on the topic of online job adverts" Debusschere et al. (2021, p. 3). Within the project, this was achieved regarding the "demand by economy sectors, professions, specific skills and qualifications, and regions" (ibid., p. 4). Within the project, it was discussed how the indicators could possibly be constructed and the challenges of doing so, including the fact that job portals are usually not designed for the purpose of data collection Debusschere et al. (2021, p. 4).

[21] See https://www.cedefop.europa.eu/en/tools/skills-intelligence/indicators

of task indices). All data is provided by one of the three European institutions CEDEFOP, Eurofound and Eurostat.

The indicators used on the platform are aggregated at the country level, the sector level or the occupational level and are available for different years.

The quality of skills intelligence depends on the quality of data available in EU surveys, such as Cedefop's European Survey for Skills and Jobs (ESJS)[22], and the Cedefop Skills-OVATE[23] project, which analyses data from online job advertisements.

The **Skills Intelligence platform** more or less presents some **general statistics** on different topics and is therefore good at providing an overview for researchers, policymakers and sector-representatives. It does prepare and present results on skill imbalances such as skill gaps of basic, transversal and job-specific skills, shares of over- and under skilled employees, skill obsolescence and skill underutilisation.

Europass

The **Europass** is targeted at individuals looking for training offers or employment in the European Union and it provides more specific information. Users can enter their qualifications and skills and get skill gap information that is concretely tailored to them. As Rentzsch & Staneva (2020, pp. 4–8) present, there are similar tools that also achieve similar functions, e.g. matching applications and job descriptions or a project that "support individual career planning" (ibid., p. 6). While the latter can support the decisions of individuals, such as those of employees or employers, platforms such as the Skills Intelligence Platform are more suitable for supporting broader stakeholder strategies and policy decisions.

Sector skills alliances: European research on skills in sectors

Another approach to collecting data has been used in activities that focus intensively on specific sectors of the economy. Within the New Skills Agenda launched in 2016, it is laid out that skills requirements differ depending on the economic sector, that technological transformation processes take place within sectors, and that sectors can maintain their competitiveness through suitable skills policies (European Commission, 2016). The central means envisaged in the Agenda's approach to sectors are sector skill alliances (also called: sector skill partnerships) funded by the ERASMUS+ programme. They are a concept for tackling skill demand and supply gaps at a sectoral level by developing blueprints for the assigned sectors with concrete

[22] https://www.cedefop.europa.eu/en/projects/european-skills-and-jobs-survey-esjs#:~:text=The%20European%20skills%20and%20jobs%20survey%20%28ESJS%29%20is,learning%20of%20adult%20workers%20in%20EU%20labour%20markets.

[23] https://www.cedefop.europa.eu/en/tools/skills-online-vacancies

measures for identifying and mitigating skill gaps. Thereby, also data are created that help to understand sector-specific situations in a more profound way. The overall aims of the projects are to identify skill gaps, develop strategies for closing these skill gaps and develop and pilot a roll-out strategy.

Having a closer look at the already existing projects, there are three basic categories of measures that projects have taken, depending on the concrete project conception and current status of the project duration, that are relevant to the topic of this document. (see for example project reports Gorni et al., 2019; Gruijthuijsen et al., 2019; Schröder, 2020; Sdoukopoulos et al., 2020). First of all, the projects depict or will depict the **status quo** regarding the supply of skills within their sector. Then, the projects define some **need for actions or recommendations** regarding future changes in skill supply. And finally, the projects develop **tools and concepts** that can be practically applied within the sector. Empirical, quantitative and qualitative methodologies are applied to gather data on a sectoral level and support these steps; e.g. surveys, interviews or further qualitative work – especially when it comes to determining the status quo or identifying needs for actions. For example, some projects mapped training courses and related them to existing European frameworks like the EQF (e.g. MATES project, see Sdoukopoulos et al., 2020, p. 122) or relevant occupational profiles that need to be specifically addressed by VET policies are identified and companies identify current and future skill needs according to a sector-specific categorisation of skills (e.g. in the ESSA project, see Schröder, 2020).

In this way, the projects provide a basis for some information on the sectoral level, which could also be included in the skills intelligence platform and used for skill research. Some of the projects have an explicit focus on the digital and/or green transitions and deliver insights into the effects of these transitions on skill demand and supply in the respective sectors, jobs and sometimes occupations.

A promising endeavour results from the activities within the skills alliance projects: several sector skill alliances are planning continuous skill monitoring and the promotion of skill development coordinated within the framework of the *Pact for Skills* (European Commission, n. y.c).

4.3 Linking of European datasets

In the BEYOND 4.0 project, for the analysis of the outcomes of digitalisation processes in the European Union, one particular interest was to analyse data on skill demand and supply together with measures of digitalisation, such as technology use and automation of tasks as well as organisational level information such as work organisation and structure of organisations. The work of WP3 identifies which European surveys include measures of digital transformation and organisational characteristics (see D3.2a, Greenan et al., 2022; see D2.2, Greenan & Napolitano, 2022a).

While some of the datasets that have been reviewed in terms of skill measurements also contain a limited number of measures for technology use and/or work organisation (e.g. certain tasks or work situations in daily working life), other European surveys have much more detailed information. This makes the linking of different European survey datasets necessary. In the WP3 of the BEYOND 4.0 project, this exercise of linking datasets has been thoroughly explored and executed to the extent that existing data allowed. It was possible to statistically link employer and employee surveys. So far, the **Beyond 4.0 WP3 dataset** was created by **linking employer and employee data**, where the dataset consists of a selection of indicators from seven different sources linked via the common cell of sector-country-year. This kind of linking of datasets allows for analysis of the effects of technology and work organisation on a number of outcomes, including different innovation measures, employment, Occupational Safety and Health (OSH), and skill match.[24]

Several **challenges** presented themselves when WP3 worked on the linking of datasets. For the purpose of understanding the effect of changes in technology use and work organisation on skill demand and skill supply on the task level, the aggregation level of this kind of linked datasets is very broad. The smallest unit of analysis that was possible to achieve are NACE sectors on the 2-digit level. This means that it is not possible to disaggregate data at the regional, company and individual levels. This highlights the need for better harmonisation of the European household and employer surveys so that it becomes possible to link datasets at a lower level of disaggregation. That is, through the linkage of more detailed common cells. Of particular relevance to this report, the BEYOND 4.0 WP3 dataset does not contain linked data to enable analysis according to the WP6 skills categorisation or a similar skills categorisation as those datasets that include indicators of different skill categories needed in the workplace were not compatible with the linked data of WP3 in terms of either point in time data collection or too small sample size to populate sector-country-cells in a statistically suficient manner. Another problem was that in some datasets the level of disaggregation of sectors was too broad.

For this particular focus, the data linking exercise undertaken by the European JRC is promising as it provides insights into tasks in jobs (Bisello et al., 2021). The European database of tasks indices across jobs in the EU15 (minus the UK) economies uses jobs as the unit of analysis (i.e. the common cell). It links information from the first cycle of the PIAAC survey (data collected between 2011 and 2018), the 2015 EWCS from 2015 and the 2012 Italian ICP occupational database on tasks in jobs. For this exercise, Bisello et al. (2021) use a taxonomy they developed for tasks, methods and tools and assign measures of the three data sources to this taxonomy. Those are then aggregated at job-year level for all of the included countries. There remain some limitations with this dataset. For example, some measures can only be retrieved from the ICP

[24] BEYOND 4.0 used data from the European Working Conditions Survey (EWCS) about tasks and matches between tasks and skills, microdata from the European Labour Force Survey (EU-LFS) was used for the change in occupational structure, technological changes were represented by company data on information technology (IT) usage (Eurostat common survey on ICT Usage in Enterprises, isoc_e), and organisation practices, including learning capacity, were operationalised using data from a combination of multiple data sources).

2012 dataset, thus representing only Italian workers, and a breakdown by individual country is not possible. However, the taxonomy includes the use of non-digital machinery and digitally-enabled machinery (where the latter can be distinguished in further detail). Data in the part of the taxonomy differentiating types of methods of work allows for some analysis of different types of work organisation and work methods. Thus, an analysis of correlations between digitalisation and tasks in jobs is possible with this new dataset. Because of the timeframe covered, it is not yet possible to track changes in tasks in jobs due to digitalisation far. This change analysis may be possible in the future if data from additional points in time is added.

Another approach to linking different datasets is the already mentioned Skills Intelligence Platform which draws on several different data sources. In this case, the presentation of data and certain results are aggregated for the platform, but there are no linked datasets available for further statistical analysis that would allow for regression analysis, for example.

4.4 Assessment of adequacy of existing data measuring skills

To be able to identify requirements for *better* data on skills, we defined the underlying overall requirements for data on skills that are important from the particular perspective that stems from the work done in work packages 3 and 6 of the BEYOND 4.0 project. There is a need for data about different **perspectives from several types of actors**, namely employers, workers, graduates and education representatives. The data should make a **clear distinction between skills and related concepts**. Related concepts, such as qualifications or occupations, should not be used as a proxy for skills**. Rather, the measurement of skills needed and used within jobs is of interest.** The data should look into skills in terms of their content and use a **categorisation of skills** along this dimension. Also, the data should make it possible to **identify skill imbalances** and, more specifically, skill mismatches and skill gaps. Therefore it also needs to measure skills of individuals or their perceived skill (mis)match with the skills needed to do their jobs. As the focus lies on the skills needed in a digitalised future, the data should include or be **compatible with data on technological change** and **changes in work organisation**. For the purpose of the European skills intelligence approach, there is a need for data from the different European member states that allow for **Europe-wide analysis** of data and international comparison of skill measures. Data should be collected **timely** and datasets should be **updated frequently**.

While there is a large amount of data on skills in the European Union, the **data itself remains very limited**. While several surveys include measures about some aspects of skills, it is not yet possible for educational systems or policymakers to adequately answer the question of how digitalisation is changing skills needs and skill supply. This limits the ability of actors to make well-informed decisions.

Stakeholders

The **relevant actors** that should be considered are currently **surveyed in parts**, but surveys are being developed for all groups we identified. There are surveys targeted at employers, employees and workers (including the unemployed), but for European country comparison, no survey asks both sides with harmonised terminologies or skill categories. The survey targeted at higher education graduates is under development (EUROGRADUATE), and the Opinion survey on VET in Europe covers VET programme graduates to some extent. A **harmonisation and coordinated data collection of these different surveys is required** to make the most of the data and allow for a more comprehensive understanding of emerging skill gaps. The job advertisement analyses represent employers' perspective and can be used to understand what skills are needed to get a job. The **Skills Intelligence Platform** uses data from different stakeholder perspectives.

The **sector skills alliances** all include employers and other stakeholder groups in their data collection. Examples for other stakeholder groups are business associations, regional policymakers, social partners and training providers. These alliances thus bring the advantage of gaining insights into even more stakeholders' perspectives into the landscape of skills data in Europe. Furthermore, stakeholders step into dialogue with each other to develop a skill strategy together for the respective sectors. As long as surveys do not provide enough detail and possibilities for linked information of the employer, workers and training providers sides, these type of data as they are produced in the sector skill alliance projects can be used to identify important skill gaps and solutions to tackle them. Here, details about skill gaps, such as **which categories of skills are needed most and which interacting skills are needed in the sectors and how to best train them can be identified**. The results also were directly presented to relevant stakeholders.

Skills operationalisation and within jobs changes

Quantifying skill gaps that arise from changes within jobs remains difficult, given the lack of suitable data and coherent categorisations of skill mismatch and employer surveys. Bisello et al.'s (2021) operationalisation of the taxonomy of tasks, tools and methods using existing data is one notable exception to a comprehensive systematic taxonomy of tasks. Despite such progress in measuring the task content of jobs, as outlined earlier in this report, tasks are not synonymous with skills.

When measuring skill needs and skill demands, the requirement is to make use of a clear distinction between skill types (such as the BEYOND 4.0 skill categorisation or a similar typology). Currently, there is **very little data on skill categories for both the demand and supply sides**. This situation makes it hard to clearly identify skill gaps that need to be addressed by the skill supply side (and is not yet being addressed). It is also **difficult to link data on skill demand and skill supply** using one skill categorisation. The categorisation of one survey is hardly compatible with other surveys' skills categories. Most surveys do not measure the whole spectrum of skill categories but include some specific types of skills in their questions.

The most **categories of skills measured** in an employee survey so far can be found in the **ESJS**, asking for digital, personal, social and methodological skills and the **PIAAC survey**, testing basic skills and digital with methodological skills and asking about social, futher methodological, and in the second wave also for socio-emotional (of which most are personal) skills. Also, the answers to the questions asking for skills needed to do the respondent's job and skills possessed by the respondent are compatible in the ESJS so that a **direct skill gap on the individual level can be evaluated** on the basis of these data. But only this year first results from the second wave of the ESJS and the PIAAC were published. When the datasets become public, changes over time in skill gaps will be possible to be analysed. The **Opinion Survey on VET in Europe does also ask about all of the mentioned skill categories** and looks at the supply side of skills. The surveys ask about the skills of the respondent, but not about skills needed in their current job, so that a skill gap analysis on the elvel of skill categories is rendered impossible. Also, on the skill supply side, the employer survey **CVTS covers all of the above skill categories except the personal skills category** and also asks for technical and job-specific skills. Here it is asked about the skills needed from the employer's point of view. It does allow for perceived skill gaps identification.

In the job advertisement analysis of **Skills OVATE**, single skills mentioned in the advertisements are collected and the results can be presented aggregated by **ESCO or O*Net skill classifications**.

The sector skill alliances use different skill categorisations. Most of them have developed their own typology according to the sectors' needs.

The Europass does refer to the EQF and fields of knowledge, but does not use a categorisation for skills of the individual user or the job offers.

Measurement of and interacting skills

All of the surveys except the PIAAC survey **do not allow for the identification of interacting skills** as they do not ask for skills in connection to (specific) tasks. The first cycle PIAAC survey explicitly **tested problem solving in technology-rich environments** which represent the interaction of methodological skills and digital skills.

The **Skills Intelligence Platform** does not give insight into skill gaps on the level of skill categories and thus does also not allow for the identification of skill needs or skill supply of interacting skills.

Europass does not allow for overall analysis of the dataset but informs job-seekers about what qualifications and knowledge they need to get a job in a specific field.

The sectoral alliance projects measure and present skill needs in different ways. Some of them did **identify skill bundles that we would classify as interacting skills** (e.g. EO4GEO, DRIVES). The approach of taking the industries' demand as a starting point and involving all stakeholders in the design of data collection and in data collection leads to the identification of the most pressing skill gaps and to the development of joint solutions for tackling those skill gaps.

Measurement of skill imbalances

We also assessed **what types of skill imbalances** are already being measured in European surveys. The labour-market relevant measures of qualifications and occupations (which are not skills themselves but proxies for skills) are the exception as they are well studied. The EU member states and the EU statistical agencies use micro-level data for the identification of the quantity of people in the EU with certain qualification levels and occupations, as well as to produce estimates on demand for workers (EU-LFS). Thus, current **skill shortages, mismatch of qualification and mismatch of field of study can be reasonably well measured**, and future projections can be produced for most member states at the EU aggregate- and national- levels.

Similarly, there is data on **perceived skill shortages of employers (ECS, MTSS, CVTS, Future of Jobs Survey)**. We found **some measures of perceived skill gaps of individuals** in the datasets of the **PIAAC** survey (digital skills), the **EWCS** (skill match with tasks and duties of a job), and **the ESJS** (asks for different skills categories needed within the job of the respondent and skill match with job). In th ESJS skill gaps can be identified for the level of skill categories, but change in these gaps could not yet be analysed as only one wave of data is public to date.

The Skills Intelligence Website of Cedefop does calculate and present skill gaps of basic skills, job-specific skills and transversal skills, under- and overskilling and underskilled at hiring, skills obsolescence and skill underutilisation based on the ESJS data (thus representing the status in 2014 so far) and over-qualification based on EU-LFS data (yearly updated).

The job advertisement data do not allow for the identification of skill imbalances.

The Europass only allows for individuals to identify skill gaps for jobs they want to get and shows skill shortages.

Analysing the effect of digitalisation on skill imbalances: linking of datasets

One obstacle to analysing the effect of digital transformation on these skill imbalances is that the **information on the influences on skill needs and supply, such as digitalisation measures, is not collected in the same surveys** as the information on skill imbalances. In order to directly analyse the impact of digitalisation (in terms of technology uptake and work organisation changes) on skill imbalances, the ability to link data from more than one survey becomes paramount. While WP3 undertook an exercise of linking a number of available datasets, and this linked data allowed better analysis of the socio-economic outcomes of the technological transformation in EU workplaces, the level of statistical data available about skills for technological transformation remains very broad (sectors in countries), so it is not possible to differentiate between regions or companies within individual countries.

These linked datasets do bring insights into country and sector differences in digitalisation and its impacts, it allows for comparing the effects of technology uptake and dominant types of organisations in sectors. Nonetheless, the datasets have the potential to provide even more fine-grained information about the topics of digitalisation, skill usage, skills demand and skill supply. The issues with linking the datasets through smaller common cells arose from the **lack of harmonisation of the different surveys and sample sizes**. These issues have already been raised in Beyond 4.0 publications of WP3 (Greenan & Napolitano, 2022a). Here, the challenges described are that the sector groupings of NACE2 were not used in all surveys, some of the surveys focused on only very few sectors, and some did re-group the NACE2 sectors, so that detail of information is lost. Then, the general issue of having too few observations to allow the analysis of more details than on the national level renders regional comparisons impossible when linking datasets. Additionally, the moments in time of data collection vary a lot between the surveys. This makes it possible but methodologically problematic to link the different surveys, depending on the topic of analysis and the surveys in question. One example is the exclusion of the PIAAC survey from the Beyond 4.0 dataset as the data collection period of the first cycle of PIAAC stretched over the years between 2011 and 2018 for one wave while the technology indicator from the ICT usage of enterprises used in the BEYOND 4.0 dataset was measured in 2010 and 2014.

Skills data for vulnerable groups

Data on skills of people in groups at risk of exclusion from the labour market can be analysed only for some of the identified groups. While age, education level and gender are included in most skill survey data, the situation of immigrants (except for the AES) and the skills of people with disabilities or chronic illnesses cannot be analysed with the current data from skill surveys.

Table 3: Measurement of belonging to vulnerable groups of the respondents

Survey	Age groups	Education level	Gender	Migration status	Disability/chronic illness
PIAAC	yes	yes	yes	no	only if inhibits employment
ESJS	yes	yes	yes	no	no
EWCS	yes	yes	yes	whether born in country of residence	only if inhibits employment
AES	yes	yes	yes	citizenship	no
Opinion survey on VET in Europe	yes	yes	no	no	no

In the skill alliance projects, the topic of inclusiveness is mainly focused on the dimension of gender, or more specifically the situation of women in sectors. No examples have been found for other dimensions of exclusion to be addressed by data collection in publications of the projects.

Timeliness of data

The data from surveys that allow for a well operationalised analysis of skill imbalances are not all collected in a timely manner. The mentioned PIAAC survey is a particularly elaborate and thus time-consuming endeavour and thus does not provide insights into short-term changes in skills. It does however provide reliable data on skills of respondents as it tests skills.

The ESJS has only been conducted twice, with a time difference of 7 years. This is not timely in the context of fast-changing sectors and jobs therein. But, most surveys in our sample are not conducted in a higher frequency. The EWCS is conducted every 5 years. On the employer side there is timely data in the MTSS as it is conducted every year, but it is not a public dataset. The ECS has only been run twice (2013 and 2019), the AES has more or less timely data from 2007, 2011 and 2016 but does not ask for skill categories. The CVTS is run every 5 years, providing comparatively similar intervals like the AES and the EWCS and uses skill categories in its measurments. The Opinion Survey on VET in Europe has only been run once so far.

All in all, a need for more timely survey data on skill requirements and skill imbalances emerges.

The data collected in the Skills Intelligence Platform is based on data sources that update their data in different intervals. The EU-LFS data, for example, delivering information on occupations and employment, is timely, while others are not.

The job advertisement analysis data at Skills OVATE is timely as accessible data is updated four times a year. But, it only generates data on the demand side of skills.

Data from the skills alliances differ in timeliness as every sectoral alliance found different solutions for data collection and data provision to stakeholders. Some of them have installed ongoing sectoral skills data collection and provision. One example is ESSA's European Steel Technology and Skills Survey and Panel that shall be continued by sector organisations after the project ends and produce data that will inform the Online Training Ecosystem through the online platform steelhub (Schröder et al., 2021).

Table 4: Summary of assessment of existing data on skills

Required topic	Available	Risk for decision making
distinction between skills and related concepts	Proxies: occupations, qualifications Tasks Few data asking employees or employers for skills needed in jobs/organisation	Overseeing changes within jobs and workplaces leading to ill-informed decisions on training and education funding and policy
Different perspectives	All there, but not connected	Bias in decision making, relying on single perspectives, overseeing misinterpretations of actors
Skill imbalances, mismatches, gaps	Not quantified, not specific (categories) Skills shortages well measured	Unclear whether we are tackling the right imbalances

Required topic	Available	Risk for decision making
Technological and organisational change as influence	Little information on technology; not linked information	We are not specific in our measures, misinterpretation of effect of digitalisation
Skill data for vulnerable groups	Some groups can be investigated, while some cannot	Risk of leaving some groups behind and/or supporting training of the wrong or not enough skill categories
Comparison between countries	Even linked data does not allow for comparisons in all aspects; lack of harmonisation (NACE2: not used in all surveys); not detailed enough	Policy differences are not in view Overall European trends not clear Role of organisations hard to test
Timing	A lot of variation	We are looking too far back, not connected/harmonised data collection Fast changes in skill gaps might be overseen

5. Conclusions: Requirements for better data on skills for digital transformation

This final section of the report sets out a summary of the requirements necessary to be able to better analyse the skills requirements and expected skills supply for digital transformation comprehensively. This includes a discussion about what additional data needs to be collected and what other requirements are needed to improve skills intelligence as set out in the New Skills Agenda of the European Commission.

Digital transformation is having a substantial impact on occupations, jobs, tools, and the organisation of work. As outlined in the previous section, there currently exist European surveys and datasets that provide data allowing detailed insights to be generated about the working lives, socio-economic situations, health and living conditions of Europeans. However, when it comes to understanding the changes that are taking place within workplaces, and more specifically, the change in the context of tasks in jobs and the corresponding skills that workers need to do these jobs, there remain gaps in the content, level of specificity, and timeliness of data.

5.1 Results of the assessment of existing data on skills

This paper outlined requirements for data on skills in Europe based on the work conducted in work packages of the Beyond 4.0 project (primarily WP 6, but also WPs 3 & 5, 4 & 8) and has assessed existing data on skills on the basis of these requirements. The perspective of Work

Package 6 of the Beyond 4.0 project was to understand changes taking place within workplaces so that European economies can prepare for, and in some cases, anticipate the skills imbalances of the workforce and citizens more broadly in such a way that all actors can share in the benefits arising from the digital transformation. Put another way, to ensure that transformation does not exclude certain groups of workers, or groups in society, creating a 'digital divide'.

The main underlying overall data requirements on skills deducted from this goal and the perspective taken were as follows. These requirements were used to assess the currently existing data and identify gaps and requirements for improvement of data. Firstly, data on skills should use a **skill operationalisation** that allows for a comprehensive understanding of skills needs and uses **within jobs,** including a **distinction of skills from tasks and skill proxies such as occupations,** asking for skills using a framework of **different skill categories,** and enabling the identification of needs and supply of **interacting skills.** They should enable the identification of **current and emerging skill imbalances**. Secondly, data should be disaggregated into groups at risk of exclusion from the labour market, such as older and younger workers, women, migrants and disabled people or people with no or low secondary education. Thirdly, it should allow for a **timely and sufficiently** updated evaluation of skill demand and skill supply. Fourth, the structure of datasets should **facilitate linking datasets from the different European surveys** to allow for skills measurement**.** Fifth, **data tools and datasets** should be **mapped in a centralised way** and made available to stakeholders in **adequate detail**. For this, data should be prepared, presented and disseminated to stakeholders in a tailored way.

The conclusions of the assessment of existing data on skills along these requirement were the following.

- Data on skill needs and skill supply is **being collected for all target groups of interest**. The best connection between different stakeholders' insights can be found in the sector skill alliance projects, but they are often limited in time and use varying definitions of skills. The Skills Intelligence Platform is a good approach to aggregate skill insights in one place, but needs more detail.
- Further **centralised overview about existing data is needed** to facilitate access to produced data and facilitate the connection of insights from different researched perspectives and levels of detail.
- Data is **not detailed enough**.
- Data on skills is **not timely enough.**
- Data from **different datasets are often not comparable**, as similar concepts are defined and measured inconsistently.
- **Skills** are often not asked for directly but instead it is **conflated with the concepts of tasks, occupations and qualifications**.
- There is a **lack of data** about skill needs and skill supply of **different skill categories.**
- There is a **lack of data about interacting skills**, especially quantitative data are missing.

- Data that **link the demand and supply side of skills is hardly existent**.
- For linking the different datasets that collect data on these two sides, in most cases, the **measurement and data collection is not compatible enough** in order to give enough detail to detect skill imbalances and changes of skill use and needs within jobs or even within companies.
- Skills data can only be disaggregated for some groups at risk of exclusion, while there is **hardly any data about skills of recently migrated and disabled people**.

After having identified these gaps in data and challenges of data collection we can formulate several requirements for better data that will be presented in the following paragraphs.

5.2 Requirements for better data on skills in the digital transformation

Based in the underlying overall requirements for data on skills and the assessment of existing data on skills as well as based on the research in WP6 (and partly WP3, 4, 5, and 8) there are several requirements for better data.

When data collection is being designed, it is vital to consider the **purpose of what the data are going to be used for** and by whom. To this end, the first requirement related to better data on skills is that **all relevant stakeholders must be included in designing data collection on skills.** This is particularly the case in relation to designing data collection via European surveys, which are complex, time-consuming to coordinate and costly to collect. Once data has been collected for these large-scale EU surveys, the questionnaire and the data are fixed, so it is not possible to change in hindsight. European statistical agencies like Eurostat and Eurofound would then need to step into dialogue with stakeholders and make use of or develop **processes of data collection design that consider the needs and perspectives of all relevant stakeholders.**

Different stakeholders need different levels of detail of data on skills. While **country comparisons** of European level data are relevant for policymaking at the European and national levels, there is also a need **for more fine-grained data at the sectoral and regional levels**. For example, sectors increasingly unite to tackle fast-changing skill needs in digital transformation. They need more detailed information of skill gaps in the different skill categories on the **sector level**. Policymakers and public agencies, such as employment agencies or economic development agencies need to understand what type of training and education they must support and extend in order to tackle the skill shortages and skill gaps relevant for the businesses in their **region** in order to secure supply of adequate workforce in the region. The skill match is important on the different levels of policy. A collection of skills data from sector and regional levels by the responsible agencies at the European Commission can facilitate a better understanding of skill gap development in the digital transformation. The aggregation of these data will also facilitate the identification of Europe-wide skill trends within sectors and common problems of regions with skill imbalances.

Overall, data that allows for the **measurement of the effectiveness of policies regarding skills** is missing. The provision of more fine-grained data and the continuous measurement of skill demand and skill supply of skill categories will help tremendously in this regard.

To understand the impact of company decisions, such as the uptake of new technology, change in work organisation and impact on working conditions, contribute to changing requirements in skill demand, skill supply and skill gaps, there needs to be data that allows for **within company insights**. Ideally, **employers and employees from the same companies need to be asked questions within one survey** so that it is possible to analyse the effects of the decisions made within companies. That is, there is a need for indicators measuring changes in both the workplace itself and the jobs of workers in those workplaces. Policymakers and data producers need to decide on this and work together to make such an endeavour possible.

At the company level, other ways of data collection than surveys allow for insights into the effects of company level decisions and the interdependent relationships of organisations, technology and humans in organisations. There are, for example, skill audits of companies, Delphi studies, horizon scanning and future scenario exercises, as well as other types of qualitative research. These non-survey types of data add important intelligence on skills that cannot be obtained from large-scale household or company surveys and should be further obtained and funded. These **data should be mapped in a centralised way** at the European level, when possible, so that researchers and stakeholders can make decisions on the most fitting data. Here, policymakers and European statistical agencies need to agree on a way forward to further work on bringing data on skill demand and skill supply together. Especially the more detailed insights into skills on sector level as they have been collected in the sector skills alliance projects should be accessible in a more centralised way. A key actor is the EACEA of the European Commission who administers the projects. Cedefop should consider using and disseminating data on skills generated in ERASMUS+ projects such as the sector skills alliances.

When it comes to quantitative data for hypotheses testing, however, there are important gaps in the existing data collected through surveys. To allow for analyses of whole economies, regions or sectors, or the comparison of company strategies that require standardised data collection and large sample sizes, it is important that data provides information for the different levels of analysis relevant to key stakeholders. This means that a further requirement for better data on skills is to ensure that for each perspective and topic (e.g. skill shortages, skill gaps, skill demand and skill supply), there are data available at an adequately disaggregated level in European quantitative surveys that facilitates unit of analyses at the country, regional, sectoral, company and individual worker levels. Policymakers and data producers should work together to ensure that all relevant levels of anaylsis of skills can use appropriate data.

As the development and implementation of extensive surveys is costly and time-consuming, especially when asking employers and employees at the same time and with different questionnaires, and with the extent of data already available when looking at the different European surveys, one requirement for better data on skills is for data producers, such as national and European statistical agencies, to improve the facilitation of linking existing datasets through improved coordination and harmonisation at the European level. The linking of employer surveys with employee or labour-force surveys allows for more topics to be analysed than with the single datasets. For the research in BEYOND 4.0 WP6, the ability to link data from employer surveys on uptake of technology, work organisation and skill needs with data from employee surveys on work, tasks and employees' skills (including the ability to undertake change analysis using multiple waves of the same surveys) would give way to an improved understanding of future skill needs and the extent and nature of changes of skill gaps.

The linking of information on the skill needs of employers and/or employees with data on the supply side of skills, such as qualification contents, skills assessment surveys and graduate surveys, will help identify skill gaps in a less biased manner than asking either only employer representatives or only employees about their perception of skill gaps. Here, the same issue of harmonisation of indicators and data collection would facilitate the linking of those datasets. This is a task of the *European statistical agencies (and the responsible policymakers* who decide on funding them), to assure that the most can be made of the existing surveys. Both need to engage in harmonisation processes and identify and implement measures to facilitate the linking of datasets.

Related to the previous point, it is necessary to make as much detail as possible in datasets publicly available to stakeholders (bearing in mind data protection regulations). The work undertaken in BEYOND 4.0 WP3 demonstrated that while a number of EU survey questionnaires contain useful measures, data protection legislation, relatively small sample sizes and lack of common definitions prevented the harmonisation and linking of datasets at the microdata level (see Greenan and Napolitano, 2022 on data servicing solutions). Particularly problematic for skills, the necessary choice of the common cell between the integrated datasets of sectors in countries does not allow a detailed analysis at the regional level, such as sectors in regions NUTS-1 level, or for differentiation between companies by size. As already presented by WP3-related publications (Greenan & Napolitano, 2022b; El-Hamma et al., forthcoming), a more flexible solution to data protection in datasets, where researchers can choose the trade-off of data detail, maintaining data privacy while gaining a level of detail for the specific research topic, would be of great advantage. Furthermore, it is worth considering expansion on the sample sizes of EU surveys, especially employer surveys, to allow for better analysis while maintaining data protection and statistical validity. Here, policymakers and data producers on national and European level need to work together to find a viable solution.

A resulting recommendation for action for European data producers is to align surveys better to enable the comparison of measurements of the same subject between countries and EU-wide. As noted in the OECD report *Getting Skills Right (OECD, 2016a)*, while many countries have skill monitoring of the labour force at the national level, and some have this information at the regional level, different concepts of skills are used. The lack of a common definition and common measures of skills hampers international comparisons. Further alignment of EU and EU member state national surveys with those of other countries would bring more detailed insights into skill gaps to assist European policymakers in identifying suitable skills development strategies. More generally, the definition of the concepts used in the different data sources on skill usage, as well as better differentiation between skills, tasks and related concepts in surveys, will result in a more precise direct measurement of skill needs and skills held by workers. The conflation of concepts hampers the statistical analysis of the interaction of different skill types, as described in D6.1 (Behrend et al., 2022). The requirement is then for data producers to clearly define the skills and skill concepts measured and differentiate between tasks, skills, and related measures such as qualifications and occupations.

The alignment of data collection points among the different main European surveys would facilitate the linking of different datasets and allow for better time-series (i.e. change) analyses. Having survey data from different surveys but from the same year makes it easier to control for external influences, such as historical events or policy changes. It also makes it easier to identify how changes measured in one survey may have been influenced by factors measured by indicators contained in another survey. Currently, statisticians are forced to use workarounds such as imputation of data from different years, and while this is workable, it is less than ideal.

One particular example of the need for an alignment between surveys is the variety of different categorisations of skill types used in different surveys. The lack of a common categorisation makes it difficult to compare skill needs and supply indicators across the various surveys, hindering understanding. The standardisation of skill categories, comparable to other international standardisations (e.g. ISCO, ISCED, DigComp) is required so it would not only facilitate the linking of datasets (thus allowing comparison of results from across different surveys), but it would also help in facilitating more systematic analyses of skills gaps. At the EU level, one possible point of reference is the ESCO classification of skills and competencies (ESCO). For worldwide comparison, the O*Net classification has reached prominence, as it differentiates between abilities, interests, knowledge, skills, work activities, work context, work styles and work values with skills in the sense that was defined in BEYOND 4.0 WP6, however, most of these categories conflate skills with tasks and tools used. Data producers and policymakers need to agree on a standardisation for skill categories.

The measurement of skills using categorisations of skills will give insights into the exact skill gaps. It is exactly the use of interacting skills from different categories needed in combination to do one task which was found to be especially important in the digital transformation. Interacting skills are needed as digital skills are increasingly needed for social interactions, problem-solving tasks and many domain-specific tasks. This observation from the qualitative research in Beyond 4.0 is not testable with the available quantitative data on skills from European surveys. Responding to digitalisation requires not only good digital skills but also non-digital skills such as problem-solving, social skills (collaboration and leadership) and personal skills (adaptability). The latest report of WP 6, the D6.1, has highlighted the need for *interacting skills*, such as the combination of digital and methodological skills or digital and professional skills. These findings shed light on a gap in current policy thinking, that is, the underestimation of non-digital skills in digital transformation. Again, the differentiation between skills and tasks and the measurement of both is necessary to identify emerging skill gaps. In order to measure interacting skills, it is not enough to ask for skill categories needed (or used) in the workplace. It needs to be clear, which different skill categories are needed in combination to do single tasks. Data producers could for example add questions to surveys that ask about specific combinations of skills or ask which tasks respondents have and which skill categories they need to do them.

Arguably, the best quality of data measuring the skills of workers involves the direct assessment of skills. One particular survey that uses this direct method of skill assessment is the PIAAC survey, however, it took seven years (from 2011 to 2018) to conduct the first wave of the survey. To better understand skills gaps arising from digitalisation, however, more timely data is required. As the method of direct assessment of skills is costly and time-consuming to conduct, so while it may not be feasible to conduct this survey more frequently, one potential solution to collecting more timely data on skills could involve the inclusion of questions on skills needed in jobs and on current skills of workers into other surveys that are conducted more frequently. In order to use these data for skill gap analyses, data producers should consider skill categories, skill levels and changes of both.

In order to understand skill gaps of groups within the population who are at risk of exclusion of the labour market, skill data should allow for a disaggregation into these groups. This is especially true for household sample survey data. From the examined household sample skill surveys, **most include the measurement of educational attainment, age, and gender while immigration status and work-relevant disabilities and chronic illnesses are not asked for**. This situation leads to a **big gap in data on potential skill divides** between these groups and the rest of the working population. Policymakers and other stakeholders currently risk to act with a gap in knowledge about these potential skill gaps of vulnerable groups. If the digital transformation should support more people of these vulnerable groups in finding decent work, this gap needs to be closed. **Policymakers need to support these processes and data producers need to include according questions into skill surveys.**

The **presentation, dissemination and accessibility of data should be tailored to suit the needs of the different key stakeholders.** If tools present only relevant data, data can be used to better support decisions in a more targeted way. To this end, Cedefop emphasises the important role of experts in helping to analyse and present data in ways that are tailored to various key stakeholders. The skills intelligence website (formerly known as the Skills Panorama), the Europass and comparable formats are examples of such an adapted use and presentation of data. This also involves different types of data because the more individual decisions are, the more detailed the supporting data has to be. For very detailed and tailored data needs, **Big Data-linked concepts** might offer solutions where representative samples, which are usually limited in sample size, cannot provide enough insight.

In summary, comprehensively analysing the skills requirements for digital transformation requires both more and better data. Stakeholders need to be involved in the design of data collection methods, data collection needs to be timelier and better coordinated, and access and dissemination of data on skills need to be better tailored to the needs of end users.

Without these improvements, the understanding remains incomplete of how and why skill needs and skill use changes over time, specifically in relation to digitalisation processes. Looking mostly at skill proxies such as occupations and qualifications bears the risk of overlooking changes that happen within occupations and within jobs. This in turn makes policymakers, taking skills-related policy decisions on e.g. vocational education and training, unemployment and employment measures, and employers, taking decisions on training and recruitment, partially blindfolded.

It is acknowledged that it is expensive and time-consuming to collect data via large-scale surveys. As long as it is not possible to collect more data on skill demand and supply with more detail, the data that is collected must be relevant in helping to understand the skills requirements arising from digital transformation. It is then necessary to better facilitate the linking of datasets, especially for key variables to be used in data integration. It is also important to gather other, more qualitative types of data on skills, particularly at the regional and company levels. As digitalisation offers the potential to open up new avenues for social inclusion, better data on skills of the groups of interest and the impact of digitalisation on traditionally disadvantaged or vulnerable groups is required. Overall, the more data is mapped and provided on the European level in a centralised way, the more can be made of data collected at company, regional, sector and national levels.

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