BEYOND 4.0

Understanding future skills and enriching the skills debate

Deliverable 6.1

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Document description

Deliverable 6.1 includes a framework for new or increasingly important skills within the digital transformation. This report updates an earlier version that was submitted in December 2019 and reflects progress and new insights. It includes results from a more detailed analysis of future skill demands performed within task 6.2 (which is based on a systematic literature review on skill needs for the digital transformation). These results were used to check and refine the skills categorisation developed in the first version of the report. Another progress was made within the chapter on the quantitative part of changes in skill demand (section 5) : The availability of data was reassessed by considering several further datasets.

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Content

Figures

Abbreviations

AI - Artificial Intelligence

API - Application programming interface

CEEMET - Council of European Employers of the Metal Engineering and Technology-Based Industries

DigComp – The digital competence framework for citizens

EC – European Commission

e-CF - European e-Competence Framework

EQF – European Qualification Framework

ESJ – European Skills and Jobs Survey

ESSA - European Steel Skills Agenda

EU – European Union

EWCS - European Working Conditions Surveys

ML – Machine Learning

MR – Mobile Robotics

O*Net - Occupational Information Network (O*NET)

PIAAC - Programme for the International Assessment of Adult Competencies

PWC - PriceWaterhouseCoopers

RBTC - Routine-biased technological change

SBTC - Skill-biased technological change

STEM - Science, technology, engineering, and mathematics

VET - Vocational Education and Training

1. Introduction

This report is an update of deliverable 6.1 delivered in December 2019. Based on the results of research activities in the first months of this work package, this report includes further insights from a systematic literature review on skills demand (s. task 6.2). Another update will follow in month 38 when data from work packages 3, 4 and 8 will be integrated into the research on future skills.

The objective of work package 6 is to achieve understanding of the new and increasingly important skills needed for future workplaces. It matches the demand side of future skills (employers´ requirements, see task 6.2) and the supply side (vocational education and training, see task 6.3). To categorise the new and increasingly important skills that are needed for digitalisation, an early framework has been developed within task 6.1. This categorisation will be described within this deliverable 6.1. After presenting general aspects of the current skills debate (section 2), the general framework will be described:

- Including the actors on the demand side and how skills demand is derived from individual and organisational requirements (section 3);
- Adding the supply side, relevant actors are described along with which topics they deal with;
- In the centre of the framework, there is a classification of future needed skills (conceptualisation);
- The quantitative part of demanded skills showing their proportions and numbers from a macro-level perspective (calculation).

The qualitative aspect of skill needs is described in section 4; the quantitative aspect in section 5. In the last section (6), the next steps will be outlined, setting out how the demand side of skills and planned updates for the skills framework will be elaborated upon in the next phase of the research.

2. Skills debate

In recent years, digital transformation has been a central topic when it comes to debates on the future demand for skills. Digital abilities of societies, corporations and individuals are a strong focus of skill definitions of this time. Aside from that, organisational change and its effects on skill demand have been widely discussed (cf. Fernández-Macías, Hurley, & Bisello, 2016, p. 33). The skills debate encompasses very different aspects, including questions of up- or down-skilling workers, types of necessary skills, gaps between skills demand and skills supply and substitution of work (Mournier, 2001, p. 1). Initial debate based on econometric modelling of the impact of advanced computerisation and automation – the so-called ‘clever robots’ – focused on occupational technological substitution and lost jobs. The message was one of looming mass unemployment (e.g., most obviously, Frey and Osborne, 2013/2017). Subsequent empirical analysis recognised the capacity for this new digital technology to destroy jobs and create new jobs and, importantly, change the task and skill composition of existing jobs (Hunt et al. 2019). This last possibility was analysed through modelling by Manyika et al. (2017) and Brynjolfsson et al. (2018), both of which concluded that fewer jobs would be lost than initially estimated by Frey and Osborne.

Also, productivity, as well as the skills of workers, are often seen as strong factors influencing progress on multiple layers (Mournier, 2001, p. 1). In a macro perspective on economic and social evolution "skill improvements [...] foster economic growth". Similarly, skill changes may also have effects on performance in organisations and corporations. And lastly, at an individual worker perspective, skill improvements may lead to higher incomes and more rewarding work. While a need to cope with societal and economic challenges may stand at the centre of efforts to shape the supply of skills, any policy has consequences which go beyond the pure change of the skills mix of workers. It may, for example, affect the design of skill provision systems (like Vocational Education and Training, VET systems), the societal value of labour, and questions of social wealth and equality. For example, it is often discussed in which way the advancing use of digital technologies may lead to an inclusion of groups that are currently excluded from the labour market (sometimes termed the digital divide). On the other hand, how the risk of exclusion and job loss are both likely to increase due to drastic changes within digitalisation is also at the centre of discussions. Thereby, not only people are affected by changing requirements for skills, but also sectors and regions and national institutions. To assess in which ways the inclusion of particular groups and regions can be assisted by the use of new digital technologies, it is important to understand how technology affects working conditions and, yet again, skill demands.

We aim to address many of these questions within the scope of consideration of our general skills framework, and the building blocks skills conceptualisation and calculations. By contributing to the skills debate, for example, by identifying important processes or defining important skills, we also understand the current skills debate as a process of social negotiation (see Mournier, 2001, pp. 46–47) accompanying and supporting the digital transformation. This being so, the following section aims to capture some of the basic concepts, phenomena, and empirical findings to further examine skill demands within the scope of Work Package 6.1 of Beyond 4.0, while the connection between skills and technological change takes centre stage. From this, it becomes apparent that the automation probability of human labour, which digital technologies may have, is at the core of the debate since different studies and concepts directly deal with possible negative outcomes of digital technologies. It shall be noted that skills stand in close connection to jobs and tasks. Therefore, employment shifts and other labour market trends can be considered as influencing factors with regard to the development of skills demands. Although some researchers use the terms "jobs" and "occupations" synonymously, jobs are occupations within industries and consist of certain tasks, as tasks can be defined as units of activity that produce output (cf. Autor, 2013). Skills are "the stock of human capabilities that allow human beings to perform tasks" (Fernández-Macías et al., 2016, p. 30) and so underpin the execution of tasks.

Job-based and task-based approach

As a first step, it is essential to envision the levels of analysis that allow us to regard the impact of technology on employment. Therefore, the job-based and task-based approaches shall be compared. The job-based approach uses jobs as the unit of analysis and mainly serves two purposes (cf. Eurofound, 2015, p. 8): on the one hand, the job-based approach is useful to describe employment shifts quantitatively, analysing *how many* jobs were destroyed and how many remain or were newly created. On the other hand, the approach is also applied to describe *which* jobs were destroyed, maintained or created, aiming at a qualitative analysis (cf. Eurofound, 2015, p. 1). As a result, the job-based approach can be regarded to assess whether or not employment structures are upgrading, polarising or downgrading and analysing the level of job churn (ibid.). The well-known study of Frey and Osborne (2013), which will be further explored within this deliverable, also uses the job-based approach to calculate the automation potential of digital technologies. Yet, different authors emphasise certain drawbacks of this approach. An important point of criticism involves the complexity of jobs and occupations, which is only considered in a limited way within the scope of the job-based approach. In this regard, Arntz, Gregory, and Zierahn (2016, p. 12) point out that the job-based approach assumes jobs to be similar across different countries and that workers within the same types of jobs have identical task structures. Bosch (2017) shows differences between occupations and jobs, which are even mirrored in different national skill formation systems.

Against the backdrop of the assumption that "workers' task structures differ remarkably within occupations" (Arntz et al., 2016, p. 12) and that, "even within occupations, workers likely are very differently exposed to automation depending on the tasks they perform" (Arntz et al., 2016, p. 12), the **task-based approach** serves as an alternative concept. In this approach, tasks that workers perform within jobs and the question of how easily these tasks can be automated takes centre stage to assess how susceptible jobs are to automation (Arntz et al., 2016, p. 12).

The task-based approach also pays tribute to the presumption that jobs change constantly and, therefore, should not be perceived as non-replenishable and static. As skills underpin tasks, the task-based approach proves useful to gain more detailed insights into actual skill demands. In an automation context, a general assumption of different authors is that particular tasks can be automated by digitalisation, while it is unlikely to automate entire jobs (Dengler & Matthes, 2015, p. 9). Still, there are some jobs which seem to be immune to technological substitution, even though these jobs may still change over time (Warhurst & Hunt, 2019, p. 8). Above that, the task-based approach plays an important role with regard to the routine-biased technological change (RBTC) approach, which will be presented in this section since it lays the foundation for the distinction between routine and non-routine tasks (Autor, Levy, & Murnane, 2003).

However, while a task-based approach can be used to classify jobs according to the potential substitution by machines and digital devices, Fernández-Macías and Bisello (2020) argue that analysis needs to move beyond a purely technical and deterministic view of jobs where they are not only viewed as bundles of tasks but also positions within the social structure of productive organisations; therefore sociological factors such as the set-up of production and service provision are key to understanding the implications of technological change on employment. In developing their taxonomy, Fernández-Macías and Bisello (2020) aim to connect the content of work (i.e. what people do at work) with its organisational context (i.e. how they do their work).

Another application of the task-based approach relevant to the skills debate is using this approach to identify which tasks in traditional 'jobs' can (or already are) being unbundled into individual tasks, which can than be performed discretely with payment made on the basis of completing the task rather than on a time-served or hours worked basis. For example, instead of a taxi driver being paid for the number of hours they work during their shift, an Uber driver is paid based on the number of individual journeys (or 'gigs') they make.

Occupational churn

As already mentioned above, the job-based approach is useful for assessing the level of job churn within particular sectors, since it helps assess how many jobs remained, were destroyed, and how many new jobs were created. With regard to the impact of new technology on human labour, there is an ongoing debate about the automation potential of new technologies. Different authors, such as the already mentioned Frey and Osborne (2013), use the job-based approach to analyse the substitution potential of digital technologies and their effects on the labour market. Within the scope of these studies, the idea of job churn plays an important role since it describes the general assumption of Frey and Osborne that jobs are predominantly destroyed due to digitalisation.

The term job churn, also referred to as occupational churn, was mainly coined by Atkinson and Wu to describe the sum of jobs lost in declining occupations and jobs added in growing occupations (Atkinson & Wu, 2017, p. 1). In this context, Atkinson and Wu state that, despite technological progress and other developments, which might enhance the decline and the emergence of jobs, the occupational churn currently reached historic lows on the US labour market (Atkinson & Wu, 2017, p. 1). Such findings indicate that technological change has not, so far, led to extreme levels of job destruction and help to perceive often cited automation scenarios more objectively.

With the scope of Beyond 4.0, we follow the definition of the European Commission's ESCO classification of skills, competences, qualifications and occupations. Therein, occupations are described as a grouping of jobs involving similar content in terms of tasks and required skills. On the other hand, a job is described as a set of tasks and duties executed by a singular person (cf. European Commission, 2018).

Upgrading, downgrading and polarisation

Upgrading describes the growth of high-paid and high-skilled jobs. Downgrading refers to job destruction at the top of the employment structure and job creation at the bottom and/or middle of the employment structure. While polarisation is understood as the decline of mid-paid/skilled jobs, leaving a residual or even expanding a number of high- and low-paid/skilled jobs (Eurofound, 2015, p. 1). More specifically, upgrading can be understood as a process that captures all employment groups in general, with new emerging tasks, which lead to a continuous upgrading of unskilled jobs (cf. Hirsch-Kreinsen, 2017, p. 7). Consequently, skill demand would generally increase, while better jobs, enriched by technology, emerge (cf. Hirsch-Kreinsen, 2016, p. 6). Yet, upgrading can also be understood as the progressive technology automation of low-skilled and low-paid jobs (Hirsch-Kreinsen, 2016, p. 5). Hirsch-Kreinsen assumes that jobs in the low-skilled area are most likely to be taken over by computer technology due to their routinised and highly rule-based character (Hirsch-Kreinsen, 2016, p. 5). Such an automation scenario fits the basic idea of the skill-biased technological change thesis, which will be further explained in the following.

The term polarisation describes the growth of high-skilled and low-skilled jobs, while the volume of medium skilled jobs decreases (cf. Warhurst, Wright, & Lyonette, 2017, p. 8, Cedefop, 2015, p. 2). Technological change can be one factor leading to skills polarisation (cf. Warhurst et al., 2017, p. 7). Skills polarisation can be seen as a potential factor for income polarisation and social polarisation, potentially undermining social cohesion (Cedefop, 2015, p. 2).

Following our intention to further explore the skills debate, we consider skills polarisation and upgrading, which seem to be the dominant scenarios at the EU Member State level (Eurofound, 2015).

It appears that skills upgrading, in the form of higher shares of employment for skilled workers, has occurred faster in more technologically advanced firms and industries (cf. Berman & Machin, 2000, p. 12). In different countries, the manufacturing sector has mainly experienced skills upgrading over the last 15 years. Consequently, low-skilled jobs are progressively automated in the process of technological change in manufacturing (cf. Gasparri & Tassinari, 2017, p. 15). Polarisation has also affected the European member states' labour markets to different extents within the last 20 years. In the United Kingdom, for example, the labour market has particularly polarised into "lovely" and "lousy" (cf. Warhurst et al., 2017, p. 8) jobs from 1994 to 2014, with an increasing concentration on lower and higher-skilled ends of the spectrum. At the same time, the recession after 2007 led to an increased level of polarisation combined with a high level of overall employment destruction in Southern European countries such as Greece, Spain, Portugal and Italy (cf. Gasparri & Tassinari, 2017, p. 15).

These findings show that polarisation and upgrading are not only understood as theoretical concepts, but as phenomena that have been visible in the last decades, since "most EU countries have experienced a variant of either upgrading or polarisation of the labour market over time" (Warhurst et al., 2017, p. 8). The underlying causes for trends in upgrading and/or polarisation are manifold, with technological change as one reason, along with other potential factors, such as globalisation, changing profile of educational qualifications or economic recessions (cf. Dachs, 2018, p. 18; cf. Gasparri & Tassinari, 2017, p. 15). Yet, in the first decade of the 21st century, empirical observations rather validate the assumption of progressing polarisation in advanced economies. At the same time, some authors assume that the increased use of digital technologies might amplify such polarisation trends (cf. Fernández-Macías & Hurley, 2016, p. 2).

Against the backdrop of upgrading and polarisation, the task-based approach proves to be useful to examine these scenarios further. It analyses changes in the combination of tasks within jobs, which we assume, might prove equally important as understanding changes between jobs.

SBTC and RBTC thesis

Related to the topics of polarisation and upgrading, there are two key debates about the automation potential of new technology and its impact on skill demands and work in general (cf.

Warhurst et al., 2017, p. 8). The first debate revolves around the skill-biased technological change (SBTC) thesis, which argues that technological change leads to job quality upgrade, with an increased volume of high-skilled workers. In contrast, the volume of low-skilled workers decreases (Warhurst et al., 2017, p. 8). Put another way, the thesis states that the progressive use of digitised technologies benefits those groups of workers who already have higher qualifications and more behavioural resources (cf. Hirsch-Kreinsen, 2016, p. 5). Therefore, the "correlation between the adoption of computer-based technologies and the increased use of college-educated labour" (Autor et al., 2003, p. 1279) could be interpreted as evidence supporting the SBTC thesis (Autor et al., 2003, p. 1279). Skill-biased technological change may also lead to differences between European states or regions. As it will be further explained within the below section setting out our "General Framework", it is expected that EU states or regions which are able to provide well-qualified workforces with digital skills will benefit from digitalisation, while those European states or regions that lack basic digital skills will be threatened by ongoing technological change (cf. Berger & Frey, 2016, p. 4).

Alternatively, the routine-biased technological change (RBTC) thesis argues that digitalisation leads to a polarisation of the labour market, since routine tasks, which are, according to different empirical findings, mainly located in the mid-skilled and medium wage area, are most likely to be automated (cf. Warhurst et al., 2017, p. 8). As a result, the thesis argues that the volume of high-skilled and low-skilled jobs increases, while mid-skilled jobs increasingly disappear due to automation (Warhurst et al., 2017, p. 8). In this sense, the RBTC thesis could be regarded as an explanation for polarisation, while the SBTC thesis promotes the idea that technology leads to steady upgrading.

It remains debatable whether routine tasks are indeed associated with skills in a linear way, as predicted by the RBTC thesis. That is, that routine tasks are mainly found in low skilled and/or low paid jobs. Some authors argue that routine and cognitive task content are similarly (albeit in reverse) linked to the relative expansion of higher-paid occupations recently witnessed in most EU countries, thereby suggesting similar occupational effects of RBTC and SBTC, and that technological factors are not the primary cause of job polarization s (cf. Fernández-Macías & Hurley, 2016).

In summary, both the RBTC thesis and the SBTC thesis say something more or less similar with respect to the top third of the skills distribution, but they differ with regard to the effect of computerisation on the bottom and the middle of the skills and wages structure. Since the RBTC thesis argues that technology substitutes for routine rather than low-skilled jobs, the theory predicts the middle rather than the bottom to shrink in relative terms (Fernández-Macías et al., 2016, p. 3). While in earlier debates, low-skilled jobs were assumed to feature a higher level of routine, the RBTC thesis argues otherwise, predicting that routine has a non-linear relationship to skills and "that technical change in the age of computerisation does not produce job upgrading or the degradation of work, but a hollowing out of the middle of the occupational structure which involves a simultaneous expansion of good and bad jobs at the same time" (Fernández-Macías et al., 2016, p. 4).

Routine and non-routine tasks

Despite the reasonable argumentation of the RBTC thesis, the assumption that routine tasks performed by low-skilled labour are most likely to be substituted by computers and advanced machinery (i.e. automated) is debatable well. It is now thought that automation may complement high-skilled workers, thus increasing their productivity (Fernández-Macías & Hurley, 2017, p. 564).

To further analyse these considerations, it seems worthwhile to consider the theoretical distinction of routine and non-routine tasks. Concentrating on the automation potential of tasks, different authors attempted to categorise tasks to explain which activities are most likely to be automated by computers within the course of technological progression and digitalisation. In this regard, the distinction between routine and non-routine tasks plays a crucial role. Thereby, the automation of routine tasks has been studied from several angles. While the noun 'routine' refers to a sequence of actions that are carried out regularly and identically, the adjective 'routine' is a synonym for 'repetitive' and 'standardized' (Fernández-Macías & Hurley, 2016, p. 3). Yet, in the scientific debate, it is important to note that the meaning of 'routine' is contested. Autor and Acemoglu for instance, define routine tasks as "sufficiently well understood that the task can be fully specified as a series of instructions to be executed by a machine (e.g., adding a column of numbers)" (Acemoglu & Autor, 2011, p. 1076; similar definitions are used by Autor et al., 2003; Autor, 2015; Dengler & Matthes, 2015). Other authors criticise the lack of a more detailed elaboration of the concepts of routine and the risk of developing a circular argument (tautology) when using the mentioned definition, connecting the term routine to the routine-biased technological change thesis: "[…] it makes the RBTC argument circular. The key point of RBTC is that computers replace routine tasks. But if we define routine tasks as those that machines can execute, the argument becomes almost meaningless." (Fernández-Macías & Hurley, 2016, p. 566; a similar argument is made by Pfeiffer & Suphan, 2015a).

Criticizing Autor's approach, Pfeiffer and Suphan (2015a) point out that the distinction between routine and non-routine tasks is insufficient to estimate the outcome of digitalisation and automation on the labour market (cf. Pfeiffer & Suphan, 2015a, p. 21). The authors then criticise that, as already mentioned, routine tasks are not clearly defined. Beyond that, the extent of routine and non-routine tasks depends not just on the level of technology-based procedures used within a certain task but also on organisational labour conditions. As a consequence, one can observe a high heterogeneity concerning the work with machines. Researching routine work with machines, therefore, requires qualitative research methods. Above that, successful dealings with complexity requires dynamic experience and not routine (Pfeiffer & Suphan, 2015a, p. 21). The German concept of "subjective work action" (Subjektives Arbeitshandeln), which Pfeiffer and Suphan developed, is based on informal, implicit and body-related qualities of humans. It assumes that the body knows, feels and internalises certain working procedures. Common sense and logic are not only helpful to decision-making in critical working situations, but intuition, emotion and instincts are also important. Thereby, the experience is a fundamental factor for employees to deal with new experiences and working challenges. In this sense, tasks once perceived to be complex can later seem routine after the worker has gained experience. While the tasks may stay the same over time, the worker may develop their own skills and experience. (Pfeiffer & Suphan, 2015a, p. 22).

Complementary to this approach, the German concept of ""Labouring Capacity Index" (Lebendiges Arbeitsvermögen) focuses on the demand side. It shows that humans need more subjective work action when working demands increase and working tools change and develop such qualities under complex working conditions. The aims at understanding how working demands change by questioning employees about the frequency in which unforeseen situations occur, how these frequencies changed over time and how they deal with complex demand structures (Pfeiffer & Suphan, 2015a, p. 23).

Manual tasks, abstract tasks and bottlenecks to computerisation

Progressing the debate away from the focus simply on routine versus non-routine tasks, Autor claims that manual and abstract tasks are those most difficult to automate (cf. Autor, 2015, p. 11). He states that manual tasks require situational adaptability, visual and language recognition[1] and in-person interactions (Autor, 2015, p. 12). These tasks are mainly found in low-skilled jobs (Autor, 2015, p. 12). According to Autor, "manual tasks are characteristic for food preparation and serving jobs, cleaning and janitorial work, grounds cleaning and maintenance, in-person health aides, and numerous jobs in security and protective services" (Autor 2015, p. 12), mostly demanding workers who are physically adept and able to communicate fluently in spoken language. Abstract tasks, on the other hand, are described as problem-solving capabilities, intuition, creativity and persuasion. As Autor states, these qualities are the main characteristics of professional, technical and managerial occupations, where workers with high levels of education and analytical capabilities are employed (Autor, 2015, p. 12). This statement is consistent with the idea that some tasks within jobs are more prone to technological replacement than others (Warhurst & Hunt, 2019, p. 26). Autor (2015, pp. 23–25) mentions different examples of Machine Learning (ML) under Environmental Control to point out that Polanyi's Paradox ("we know more than we can tell") can and has been overcome and that even non-routine tasks can be automated. Frey and Osborne (2013) corroborate this statement, saying that "recent developments in ML and mobile robotics [MR], building upon big data, allow for pattern recognition, and thus enable computer capital to rapidly substitute for labour across a wide range of non-routine tasks. Yet, some inhibiting engineering bottlenecks to computerisation persist. Beyond these bottlenecks, however, we argue that it is largely already technologically possible to automate almost any task, provided that sufficient amounts of data are gathered for pattern recognition" (Frey & Osborne, 2013, p. 24).

Frey and Osborne's study "The future of employment" (2013) can be seen as one major reference within the debate about the automation potential of tasks. In their study, the researchers revisited Autor's task model and identify tasks that are highly susceptible to automation through ML. Therein, they also described engineering bottlenecks that defined the limits to automation in the year of publication. In total, they examined the tasks of 702 detailed occupation descriptions of the O*Net database of the US Department of Labor (Frey & Osborne, 2013, p. 22). They assessed the occupations using two methods: First, they arranged a workshop in which researchers reviewed all of the occupational descriptions and labelled them according to the number of tasks that could be automated and, secondly, they screened for tasks that could not be automated due

[1] Even though visual and language recognition can be accomplished by AI these days.

to engineering bottlenecks[2]. By doing so, they estimated that 47% of the existing jobs in the USA were highly susceptible to being automated, implementing recently developed technologies or technology implementations based on ML in an unspecified time frame. Frey and Osborne's so-called bottlenecks to computerisation categorise three fields of non-susceptible labour inputs: Perception and manipulation tasks, creative intelligence and social intelligence tasks (cf. Frey & Osborne, 2013, p. 31). Thereby, Frey and Osborne's concept of perception and manipulation tasks, which encompass finger dexterity and manual dexterity, is closely connected to Autor's idea of manual tasks. The field of creative intelligence, encompassing originality and fine arts and social intelligence, which encompasses social perceptiveness, negotiation and persuasion, is closely connected to Autor's idea of abstract tasks (Frey & Osborne, 2013, p. 31).

Taking the above into account, views on which tasks are most likely to be automated differ depending on the author's perspective on topics like, for example, upgrading and polarisation and the approach that has been used (Arntz et al., 2016; Autor, 2015; Fernández-Macías & Hurley, 2016; Frey & Osborne, 2013). Aside from that, it is of significant importance that sectors are analysed in the respective study since different labour market sectors differ regarding skill demands in terms of technologies in use and production structures. For example, the results of Pfeiffer and colleagues' study "Qualifikation 2025" are oriented towards the analysed industrial sectors of machine engineering and plant engineering, which makes it difficult to extrapolate the particular findings of this study to other sectors (cf. Pfeiffer, Lee, Zirnig, & Suphan, 2016). Even though the introduced task models and assessments with regard to the automation potentials can be criticised for their limited explanatory power, they serve as an orientation for further analysis, especially in terms of calculating the outcomes of digitalisation.

3. General Framework of Skills Demand and Supply

A central topic of task 6.1 (and thereby of this deliverable) is to develop an early classification of skills for the digital transformation. Based on desk research, literature has been evaluated to collect all characteristics of skills that are associated with the digital transformation. Many classifications exist already. So, the first challenge was to review the different classifications and build one that combines and/or reconciles these existing classifications to serve as a common basis for understanding how to conceptualise future skills requirements within the BEYOND 4.0 consortium. This classification is considered the qualitative component of the general framework to be developed, calling "conceptualisation". The next building block is the quantitative part of the work programme called "calculation". This part should deliver the quantitative structure to estimate how many jobs will be affected by digital transformation. That means to examine how many new jobs might emerge, how many jobs will be destroyed, how many jobs will substantially change and how many will incrementally change over time. This approach will explain what kind of skills change (upskilling, reskilling etc.) is needed and to what quantitative extent. In analysing occupations and the bundle of tasks they comprise to estimate the risk of automation, Frey and Osborne (2013)

[2]These bottlenecks centred on finger dexterity, manual dexterity, cramped work space, awkward positions, originality, fine arts, social perceptiveness, negotiation, persuasion and assisting and caring for others (Frey & Osborne 2013, p. 31)

concluded that computer technologies could potentially substitute 47% of the employment of the United States. This type of forecasting has a number of implications for the extent to which skills will be needed in the future and which occupations may become obsolete. Frey and Osborne (2013) 's methodology has often been criticised, and therefore other methodologies have to be considered to estimate the quantitative structure of skill demands in the digital future. So, conceptualisation and calculation have been defined as two building blocks of a general framework for progressing theoretical and empirical understanding of new and increasingly important skills in the digital transformation (see Figure 1 below).

Figure 1: Building blocks of the general framework of skills demand and supply.

The next step is to prepare the framework for the following tasks within the work package "Understanding Future Skills". To avoid – or at least minimize - mismatches between required and available skills in the digital transformation, the demand side and the supply side of future skills have to be aligned (i.e. skills equilibrium). On the demand side, the requirements of employers have to be estimated. On the supply side, the consequences for the national VET systems have to be estimated to fulfil the employers´ requirements.

Green's framework of "skill formation and the deployment of skilled labour" (Green, 2013) provides a useful 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. Even though we have already identified these two markets, Green's framework offers an interesting approach to incorporating our skill framework.

On the one hand, Green portrays employers' demand for skills. Two types of employees´ needs have to be distinguished: the skills ***to get*** the job and the skills ***to do*** the job (Warhurst & Luchinskaya, 2018). There can be a difference between the two with, for example, employers requiring employees to have completed a university degree to get the job despite the tasks involved in performing the job being sub-degree tasks (e.g. James, Warhurst, Tholen, & Commander, 2013). And there is the workers' skills demand, referring to the ongoing need for workers to increase their skill level to remain employable in the labour market. Consequently, we adjusted our skills framework, distinguishing between individuals' and organisations´ demand for skills (as a starting point for employers' demand for skills). Both types of skill demands have to be explained in detail.

The individual´s demand for skills is triggered by future jobs comprising changing tasks that require new or modified skills. These jobs might be changing due to new technologies, reorganisation of work or other employer-related reasons. Management decisions could lead to job displacement, job replacement, or changes in the current job's work content (e.g. job enrichment). All of these decisions could create new tasks, and new skill demands to complete the tasks. Alternatively, there is also a demand for job changes by the individuals. Individuals might be interested in moving to a new job to advance their professional career or initiate a new career that is better suited to their personal and/or family circumstances. Moreover, the emergence of the platform economy and digital platform-mediated work might very well influence the skill demand and the skill set needed of the so-called gig-workers.

Estimating the future skill demands of employers is difficult, so forecasts are often quite crude. To derive skills demands more systematically, we are using the "Digital Capability Reference Framework" (European Commission, 2019, pp. 20–29). As a starting point, the framework uses the **digital capabilities of an organisation** that it uses to tackle the digital transformation. It comprises 24 IT capabilities in 9 areas, such as data management, innovation management or (cyber) security management. Theses "digital capabilities reflect the ability of an organisation to systematically and repeatedly mobilise processes, people and technology towards achieving specific outcomes." (ibid, p. 20). So, at an organisational-level, these are abilities address the challenges of the digital transformation. At the next level, **competences** can be identified that are needed to build up the organisational digital capabilities of an organisation. These are individual competences taken from the European e-Competence Framework (e-CF), comprising **general and comprehensive e-Competences** at different proficiency levels (which are matched to the European Qualification Framework EQF) as well as from the Digital Competence Framework for Citizens (DigComp2.1) also using EQF-compatible proficiency levels and providing a better operationalisation of basic digital skills. Furthermore, **roles and job profiles** can be defined that should include the defined competences. For instance, cyber security and related e-Competences might be related to an IT security manager. This job profile comprises a general mission and a list of tasks to be completed. This systematic review has been applied within the industry-driven definition of employers´ requirements being done in the Blueprint-projects of ERASMUS+. For instance, the project ESSA (Blueprint "New Skills Agenda Steel"[3]) distinguishes current tasks and future tasks of employees. As tasks are viewed as changing, future skill needs are defined at different proficiency levels. In terms of digital skills, this requires a **distinction between basic and advanced digital competences**, which we have taken into account in the classification of skills that have either recently become required or are likely to become more important in the future (s. section 4).

On the supply side, providers of education and training are in charge to fulfil the organisations´ and individuals´ requirements on training (cf. Felstead, Gallie, Green, & Inanc, 2013, p. 2). The VET systems of the member states have to adapt their training regulations, curricula, training methods and teaching tools to the requirements of digitalised working processes. The same applies to higher education, where universities have to take up the demand for new or substantially changing occupations (such as data scientists) and integrate digital content and new working styles into their curricula. Companies (and other organisations) also serve as providers for skills – by vocational training in companies, by learning on the job and by close cooperation with external training providers (e.g., offering internships). Companies use leeway within training regulations to adapt education in the VET systems and universities to their own needs. For instance, some (German)

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[3] The ESSA project has received funding under the European Union's ERASMUS+ program under grant agreement No. 600886).

companies in the steel sector extend initial training in the VET system with additional training modules (of two months) to develop missing digital skills.

The European Union (EU) provides guidance on how member states can develop their VET systems and higher education to meet the needs of companies and help individuals prepare for the future labour market. By developing policy, research and innovation programs and funding schemes, and developing a common framework and qualification standards, the EU can influence the direction of future skills development. Published in February 2020, the European Commission's *Shaping Europe's Digital Future* communication sets out the three key objectives the Commission will focus on for digital transformation and the key actions associated with each of these objectives (European Commission, 2020). For example, the new EU budget will tackle digital skills gaps by funding targeted programmes such as:

- the new *Digital Europe Programme* (targeting Masters programmes in advanced digital technologies, short-term specialised training courses in advanced digital skills and job placements where digital technologies are being developed or used),
- the *European Social Fund Plus* (supporting member states to improve national education and training systems to support the acquisition of key competences, including digital skills, and promote upskilling and reskilling opportunities for all, emphasizing digital skills),
- the *European Social Fund Plus* (supporting member states to improve national education and training systems and promote upskilling and reskilling opportunities, placing a particular emphasis on digital skills),
- and the *European Global Adjustment Fund* (to support training with a digital skills component to help laid off workers find another job or set up their own business).

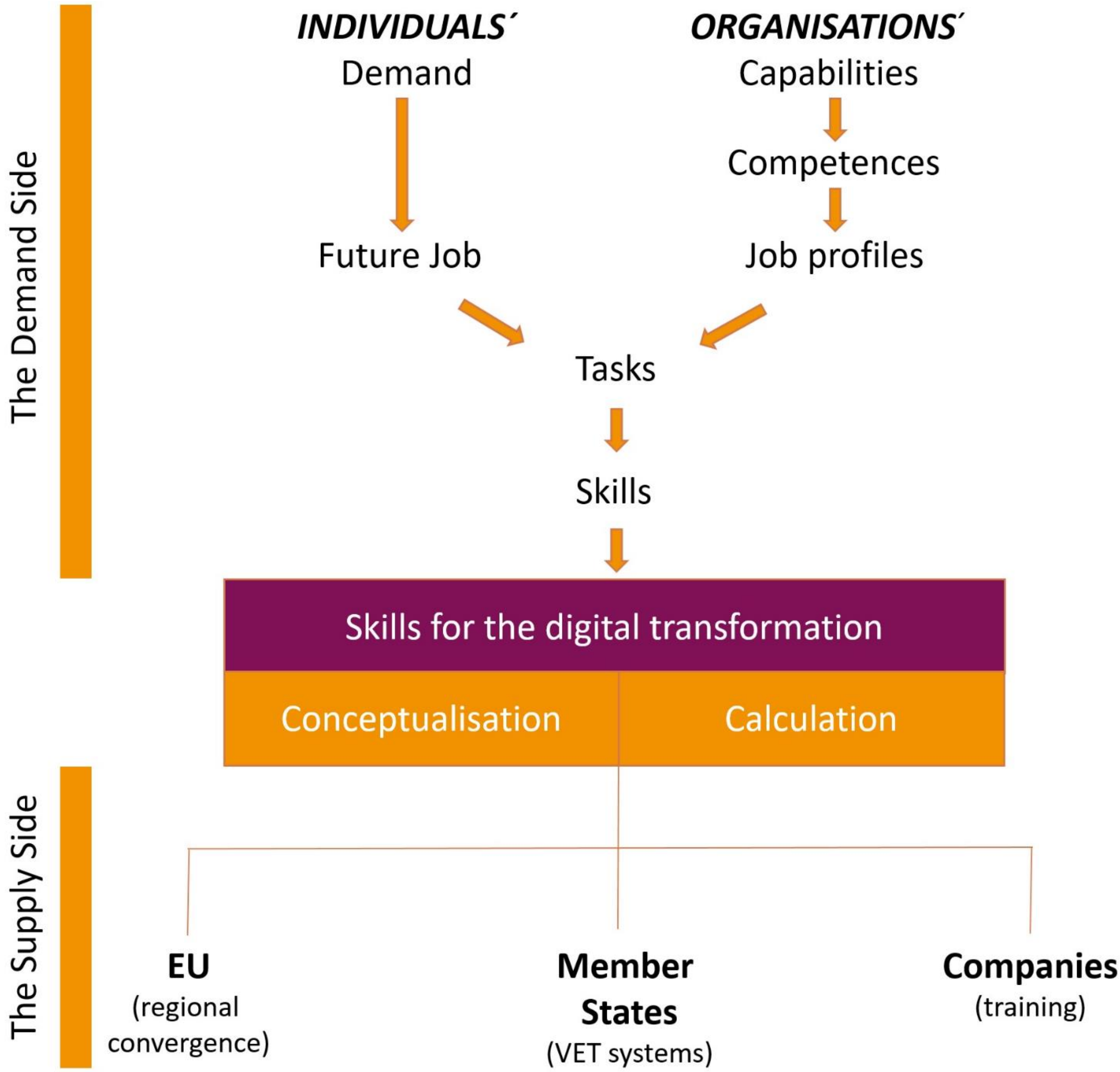
Moreover, the EU's new *European Skills Agenda* includes objectives for the skills for jobs in the digital and green transitions while the *Digital Education Action Plan* (2021-2017), aimed at making education and training fit for the digital age, calls on member states and stakeholders to work together to develop high-quality, inclusive and accessible digital education in Europe. Furthermore, the new *Digital Skills and Jobs Platform* will act as a centralised resource for digital skills training and resources in Europe.

Ultimately, though, it is the member states' responsibility to adapt and provide training and education for their citizens, enabling them to participate in public life and employment. Laws and regulations determine how the VET system is structured, how well training and education institutions are equipped and how accessible education is and are decided on by member states or even smaller administrative districts. These institutions strongly influence the skill supply and skill demand by deciding on certain development strategies and setting agendas.

Based on the assumption that SBTC is taking place, this development creates differences between member states and between regions within member states throughout Europe (Berger & Frey, 2016, p. 4). It is to be expected that those regions which have a digitally-skilled workforce will benefit from technological change. There are regions in the EU whose workforce lack basic (digital) skills. These regions are threatened to lose further ground in the digital transformation if the EU and its member states do not take countermeasures here. It is one of the challenges for the EU to oversee regional convergence. Berger and Frey (2016, p. 5) state that the diffusion of skills is key for job creation and shared economic prosperity. All in all, closer coordination between the different actors on the supply side is needed to meet the digital transformation challenges.

Our general framework helps to understand the method of identifying the skills of the future as a joint task for a range of actors from different sectors at the national level, including workers and employers on the demand side, as well as EU member states' policy makers, national VET systems, educational institutions and companies' training on the supply side (see Figure 2 below). While Green's framework aims at identifying the factors that shape the types and levels of skills that people acquire, our framework directly aims at enlisting new skills that are necessary for, become more important, or are newly requested within the scope of the digital transformation.

Figure 2: General framework of skills demand and supply.



4. Developing a Classification of Future Skills

As part of the general framework presented above, a conceptualisation was developed, which categorises new or increasingly important skills that are perceived to be necessary for digital transformation. In doing so, we focus on Industry 4.0 (digitalisation of manufacturing and changing work content) as well as the platform economy. The latter, however, to a lesser extent because the literature on the subject remains scant.

Literature search

Our classification should be compatible with entrepreneurial decision-makers, employees, employers, and educational institutions to support and guide their training content, job definitions, and work tasks. In the following section, different characteristics of our classification shall be further explained while we compare these features with the categorisation of other skills frameworks. This way, we are able to display the development process while also reflecting on the specifics of our framework:

- Beyond reviewing the current literature and examining different data sources for the first report submitted in December 2019, this update of deliverable 6.1 includes insights from a more detailed analysis of future skill demands performed within task 6.2. The update of D6.1 is based on a systematic literature review on skill needs for the digital transformation. We used the scientific literature search engines SCOPUS and WEB OF Science to identify relevant literature, and we applied a searching code that covered the three topics skill demand, working life/industry and technology. We have extended the search to Google Scholar to take the literature into consideration which is not a peer-reviewed publication but still relevant as Google Scholar shows reports of relevant institutions such as Cedefop, Eurofound, OECD. The Google Scholar search produced more than 40,000 hits, so we considered only the first 30 pages containing the most relevant hits.

- The remaining 1.374 hits were filtered: duplicates were removed, articles/reports published before 2010 were sorted out. Also, purely technological oriented publications not referring to skill needs and publications that did not include relevant terms in the heading were not considered further analysis. For the remaining publications, the relevance to our object of investigation was assessed along with defined criteria - leaving 50 publications that we have considered for this deliverable in more depth. While reading the articles, their references to other relevant publications were taken up and evaluated in this report.

As results from WP3, 4 and 8 are not yet available, it was not possible to incorporate their findings into this version of our framework. A systematic analysis of the interviews conducted in WP4 and WP8 will be incorporated into the final report to be submitted in month 38.

Based on the sources reviewed to date, we found that most authors concentrated on the demand for skills from an employer's perspective (Acatech, 2016; Cedefop, 2015; Pfeiffer et al., 2016; Probst et al., 2018, 2018; Servoz, 2019; Spöttl, Gorldt, Windelband, Grantz, & Richter, 2016; World Economic Forum, 2016). Additionally, we identified several sources that deal with skills from an employee´s perspective, such as the European Skills for Jobs Survey (ESJ; Cedefop 2016). We analysed these different frameworks to develop a coherent categorisation for future skills. Up until this point, our skills classification is demand-based, however, we are preparing compatibility with the supply side to directly link the two markets with each other (task 6.3 is currently being working on).

The Development Process of a New Classification of Future Skills

The classification is based on a body of literature that deals with the consequences of digitalisation on future skills. Whilst digital skills may take centre stage at many future workplaces, there are various other skills, such as social skills as well as numeracy and literacy, that become increasingly important as well (Berger & Frey, 2016; Deming, 2017; Kirchherr, Klier, Lehmann-Brauns, & Winde, 2019; Probst et al., 2018).

These other skills are not directly linked to specific digital technologies but become more important due to an organisational transformation that accompanies the digital era (Dhondt, van der Zee, Preenen, Kraan, & Oeij, 2019, pp. 197; Fernández-Macías et al., 2016, pp. 33–36).

In this context, we paid attention to various T-shaped skills models that can often be found in the literature (e.g. Pfeiffer et al., 2016; Probst et al., 2018; Rampelt, Orr, & Knoth, 2019). The notion of T-shaped skills distinguishes between general skills (often referred to as transversal or non-technical skills), which are used across different domains, occupations and professional skills (often also referred to as job-specific or technical skills), which are only used in certain domains. These are often called professional skills.

Our desk research initially created the impression that the differentiation between professional (or domain-specific) and general skills plays a minor role in the skills we categorised. In digital transformation, literature is focused on digital skills and non-technical skills, often called complementary skills or soft skills covering social, cognitive and personal skills. As there are myriad occupations, and according to professional skills (Handel, 2012), it is impossible to systematically analyse the change of professional skills. Thereby, our main objective is to concentrate on skills that are not specifically related to particular domains or jobs. Nevertheless, we recognised that professional skills, in general, are still important in the digital transformation. Professional skills have not become apparent at an EU or international level but the sectoral and company level. When analysing literature on sectoral level (e.g. in the Blueprint-Projects as part of the New Skills Agenda for Europe) and analysing projects at the company level, we found some evidence for intertwined skills digital and professional skills in changing work tasks of the steel sector (https://www.estep.eu/essa/essa-project/). The following shows which distinctions are made regarding future demanded skills and how these can be brought together into a unified classification of skills. While doing so, we take new skills into consideration and well-known skills that are gaining importance in times of digital transformation.

There is currently much debate about T-shaped skills, with various models offered to divide two types of skills. Rampelt et al. (2019) make a distinction between specific skills (for a certain field of work or discipline) and general skills (fundamental skills, such as numeracy, literacy and transversal skills). From the authors´ point of view, there is a greater need for hybrid skills, which means a "domain know-how in an engineering discipline paired with solid basic knowledge in digital disciplines" (Gallenkämpfer et al., 2018; see also General Assembly and Burning Glass, 2015). In this sense, digital skills are understood as general skills. This approach reflects the traditional understanding of T-shaped skills. The vertical bar represents the depth of professional skills, and the horizontal bar stands for broad non-domain specific skills (s. Warhurst, Barnes, & Wright, 2019).

On the other hand, Pfeiffer et al. (2016) distinguish between professional skills and transversal skills, which could be perceived as the vertical and horizontal bars of the T-shaped model. Digital skills could be both professional skills (digital skills related to one specific technology) and transversal skills (general digital skills related to different digital tools such as data privacy or dealing with big data). Transversal skills include interdisciplinary collaboration and innovation capacity of employees. Pfeiffer and colleagues (2016) stress the meaning of an interface between IT skills and professional process and practice skills in relation to transversal skills. These findings confirm the need mentioned above for intertwined (digital and professional) skills. Since in the context of industry 4.0, especially of cyber-physical systems, physical processes and their digital representation are closely linked, the connection between professional skills and digital skills also experiences a considerable increase in significance. So, we had to keep in mind to cover the relationship between professional skills and digital skills in the classification of skills needed for the digital transformation (which also suggests using the T-shaped model).

Kirchherr et al. (2019) make a T-shaped based differentiation between single tech-specialists and many employees with digital and non-digital key competences. The authors only analyse skills that are needed across a wide range of industry. They do not include domain-specific or industry-specific skills. So, this approach can be understood as a characteristic of the T-shaped model but defined as deep and broad skills and not domain-specific and general skills. Berger and Frey (2016) differentiate between digital hard skills (STEM, advanced IT skills) and soft skills (cross-functional skills such as emotional intelligence and innovative skills). CEEMET (2016, p. 6) makes a similar distinction, stressing the combination of hard skills (generic technical skills, coding skills, analytical skills to making sense of data) and soft skills (ability to cooperate, problem-solving ability, ability to communicate). Different literature sources also acknowledge transversal skills as important in the digital future. For example, Servoz (2019) lists social and creative intelligence as meaningful, while Acatech (2016) identifies interdisciplinary thinking and acting, problem-solving and optimisation skills, and process know-how as important for digitalisation. Bakhshi, Downing, Osborne, and Schneider (2017) stress the growing importance of non-cognitive skills, including social skills and leadership skills. Windelband (2019) emphasises thinking in networked systems or holistic thinking in process contexts as requirements for digital transformation skills. This strand of the literature shows that digital skills are needed for the digital transformation, and analogue skills, such as social skills, creative skills, and problem-solving skills, are also needed.

However, there is much literature that emphasises the combination of digital skills and analogue skills as an important requirement for digital transformation. Some call them (Rampelt et al., 2019), some a mix of basic, soft and digital skills (Servoz, 2019); others name it 21st-century skills (mix of information, media, technology, learning and innovation skills such as communication, and critical thinking). Van Laar, van Deursen, van Dijk, and Haan (2017) elaborated a classification of 21st-century skills. However, they focus on digital skills so that the analogue skills only appear as contextual skills in their framework. Typical analogue skills, such as critical thinking, problem-solving, communication, collaboration and creativity, have only been considered to the extent that they include the use of ICT. Also, Agoria, Belgium's largest employers' organisation and trade association, has developed a digital skills model that could be considered for the BEYOND 4.0 classification. Currently, it is only available in French and Dutch. Therefore, further development must be awaited.

Berger and Frey (2016) demand fusion skills as a mix of creative, social and technical skills for digital transformation.

Discussing different options for categorising future skills

In this section, we present and discuss different options to build categories for future skills:

- Probst et al. (2018) developed a framework that covers a broad range of future skills and represents high-tech T-Shaped skills.
- Van Laar et al. (2017) conducted a systematic literature review on 21st-century skills and derived a digital and contextual skills classification.
- Fernandez-Macias and Piselo (2020) developed a task-based approach that includes physical, cognitive and interactive tasks requiring related skills.
- Finally, we present the results of Janis/Alias (2018), who derived a classification from a systematic literature review that covers digital skills and four main categories of analogue skills required by the Industry 4.0: the personal, social, professional and methodological competencies skills.

Based on these different concepts, we have identified a classification that is best suited to the BEYOND4.0 approach.

Skills for Smart Industrial Specialisation and Digital Transformation

On behalf of the European Commission (Directorate General for Internal Market, Industry, Entrepreneurship and SMEs), the Executive Agency for Small and Medium-Sized Enterprises (EASME) undertook a research project aimed at developing a toolbox for high-tech skills development for smart industrial specialisation and digital transformation (Probst et al., 2018).

The project's findings support the view that skills requested by industry are not limited only to technical skills. The approach developed by the project is based on T-shaped skills taking up the concept of specialist skills within one domain combined with general skills across multiple domains (Probst et al., 2018). In smart industrial specialisation and digital transformation, they developed a concept of high-tech T-shaped skills. This concept combines high-tech skills with specific complementary skills. Technical skills are basic digital skills (user skills), advanced digital skills (relevant to IT professionals or high-touch jobs with complex software or machinery), and skills relevant to researching and developing production technologies, digital technologies and cyber-technologies.

Complementary (analogue) skills are related to quality, risk and safety, communication skills, entrepreneurial skills, innovation skills, emotional skills, skills in an adjacent technology and/or system of thought, and the ability to consider ethical implications). Among high-tech employers in Europe, some have shown that "a strong positive sentiment towards" these complementary (analogue) skills are needed (Probst et al., 2018, p. 213).

Figure 3 presents a table with a collection of those high-tech skills in demand with a dichotomy made between technical (1) and complementary categories of skills (2 through 7):

Figure 3: Skill Categorisation by the EU project "Skills for Smart Industrial Specialisation and Digital Transformation"

1. Technical	2. Quality, risk & safety	3. Management & entrepreneurship	4. Communication	5. Innovation	6. Emotional intelligence	7. Ethics
Competences related to practical subjects based on scientific principles (e.g. characterisation, systems integration, mathematical modelling and simulation, top-down fabrication, etc.)	Competences related to quality, risk & safety aspects (e.g. quality management, computer-aided quality assurance, emergency management and response, industrial hygiene, risk assessment, etc.)	Competences related to management, administration, IP and finance (e.g. strategic analysis, marketing, project management, IP management, deal negotiation skills, etc.)	Competences related to interpersonal communication (e.g. verbal communication, written communication, presentation skills, public communication, virtual collaboration, etc.)	Competences related to design and creation of new things (e.g. integration skills, complex problem solving, creativity, system thinking)	Ability to operate with own and other people's emotions, and to use emotional information to guide thinking and behaviour (e.g. leadership, cooperation, multi-cultural orientation, stress-tolerance, self-control, etc.)	Ability to consider the ethical impact of job tasks and new technologies and applications on society.

Source: Probst et al. (2018, p. 221) adapted from European Commission 2016 Final Report: Skills for Key Enabling Technologies in Europe: Vision for the Development of Skills for Enabling Technologies (KET)

The above figure gives the impression that no job-specific professional skills are included in this categorisation. But, taking a closer look into the full list of characteristics of a category refutes this impression. Technical skills are overarching a broad range of skills related to digital technologies, cyber technologies, and production technologies. And even if this is not explicitly stated, the above-mentioned framework (Probst et al., 2018) includes professional skills. Production technologies even comprise chemistry, physics, engineering and biology, which is usually understood as professional knowledge and skills. Furthermore, skills for equipment running, operation monitoring, troubleshooting, maintenance, and repair are traditionally industry-specific or even job-specific skills (see figure 4). For Beyond 4.0's classification of skills, the differentiation between professional skills and analogue skills need to be clearer and more easily identifiable.

Figure 4: Sub-areas of technical skills.

1. TECHNICAL	
1.1 Production technologies	**1.2 Digital technologies**
Chemistry	Physics
Physics	Engineering (incl. Systems Engineering)
Engineering (incl. Systems Engineering)	Electronics
Electronics	Optics
Biology	Photonics
Optics	Computer science
Photonics	Nanoscience
Computer science	Materials Science
Nanoscience	Mathematics
Materials science	Statistics
Mathematics	Microelectronics
Statistics	Design Methodology
Metrology	Operations Analysis
Big data analytics	Systems Analysis
Business analytics	Computer-Aided Design (CAD)
Microelectronics	Multidisciplinary design optimisation
Design Methodology	Process Layout & Optimisation
Operations Analysis	Life-cyle analysis
Systems Analysis	Scalability analysis
Computer-Aided Design (CAD)	Computer skills
Multidisciplinary design optimisation	Programming
Process Layout & Optimisation	Computational thinking
Life-cycle analysis	Mobile app design and development
Scalability analysis	IT and platform architecture
Computer skills	Enterprise resource planning
Programming	Artificial intelligence
Computational thinking	Complex business systems
Mathematical modelling and simulation	Big data analysis
Computer-Aided Engineering (CAE)	Business analytics
Non-destructive testing	Internet of Things
Real-time modelling and simulations	Systems integration
Process improvement tools	Characterisation and analysis
Computer-Aided Manufacturing (CAM)	
Systems Evaluation	
Standard Operating Procedures (SOP)	
Product labelling and packaging	
Top-down fabrication techniques	
Equipment Selection	
Installation	
Equipment running skills	
Operation Monitoring	
Troubleshooting skills	
Maintenance, Repair and Overhaul (MRO)	
Systems integration	
Characterisation and analysis	
General Lab Skills	
Specific Lab Skills	
1.3 Cyber technologies	**1.4 Thematic domains**
Engineering (incl. Systems Engineering)	Environment
Computer science	Energy
Design methodology	Mobility

Systems analysis	Health and wellbeing
Cyber technologies	Food and nutrition
Computer skills	Security
Programming	Privacy
Computational thinking	Inclusion and equality
Cloud computing and virtualisation	
Security skills	
IT and platform architecture	
Web development	
Internet of Things	
Social media	
Mathematical modelling and simulation	
Systems evaluation	
Systems integration	
Characterisation and analysis	
2. QUALITY, RISK & SAFETY	
2.1 Quality	**2.2 Risk and Safety**
Quality management	Risk Assessment
Quality-Aided Quality Assurance	Working Conditions/Health and Safety
Quality Control Analysis	Emergency Management and Response
	Industrial Hygiene
	Equipment safety
3. MANAGEMENT & ENTREPRENEURSHIP	
3.1 Business Development	**3.2 Operational Management**
Strategic analysis	Project management
Technology strategy	Time management
New Product and Process Development (NPPD)	Teamwork skills
Marketing	Coaching & developing
Customer focus	Delegation skills
3.3 Entrepreneurship	Monitoring
Deal negotiation skills	Risk management
Acquisition of funding	Management of personal resources
Intellectual Property (IP) management	Management of financial resources
Internal regulatory affairs	Supply chain management
	Cost modelling skills
	Generation of shop floor work instructions
	Procurement skills
4. Communication	**5. Innovation**
Interpersonal skills	Integration skills
Verbal communication	Design mind-set
Written communication	Continuous experimentation
Presentation skills	Complex problem solving
Public communication	Creativity
Virtual collaboration	Systems thinking
6. Emotional Intelligence	
6.1 Self-managment	**6.2 Social skills**
Persistence	Friendliness/being respectful of others
Passion, enthusiasm & curiosity	Leadership
Sense of responsibility	Integrity
Stress tolerance	Cooperation
Attention to detail	Multi-cultural/global orientation
Adaptability	
Ability to thrive on failures	

Balancing life and work demands	
Self-discipline	
Self-control	
Proactivity	
Continuous improvement orientation	
Active Learning	
Alertness	
Judgement and decision making	
7. Ethics	
Basic human values	
Empathic concern	
Perspective taking	
Moral behaviour	
Moral cognition	
Moral judgement	

Source: Probst et al. (2018, pp. 228-230)

The classification of Probst et al. (2018) covers a broad range of future skills for the digital transformation, and its main categories are well operationalized. However, there is no clear distinction between digital skills and other technical skills that correspond to professional skills. As mentioned above, a differentiation between digital skills and professional skills is very useful to clarify the relationship between both categories. While Probst et al. (2018) offer the presented categories, they did not collect data to which extent skills of these categories are required or will be required in the future. So, it seems not to be a proper classification that can be used for task 6.2, in which we are analysing which skills will increase in importance and which ones will decrease. Further options for categorising future skills are to be considered.

Categorising 21st-century skills (Van Laar et al., 2017)

Van Laar et al. (2017) carried out a systematic literature review to "identify the concepts being used to describe the skills needed in a digital environment, go beyond mere technical use, and focus on 21st-century digital skills" (p. 582). The research was premised on the assumption that 21st-century skills are needed by employees to be prepared for the changing requirements of their jobs. The systematic review of the literature includes peer-reviewed articles from 2000 to 2016. The theoretical framework identified various concepts: 21st-century (learning or thinking) skills, digital competence, digital literacy, digital skills and e-skills. Moreover, they found that concepts are moving into the direction they consider knowledge- or content-related skills. In examining the relationship between 21st-century skills and digital skills for knowledge workers, Van Laar et al. (2017) proposed a framework of 21st-century skills that is far broader than digital skills, where 21st-century skills are not necessarily underpinned by ICT. The framework identified seven core skills: technical skills, information management, communication, collaboration, creativity, critical thinking, problem-solving (Figure 5) and five contextual skills: ethical awareness, cultural awareness, flexibility, self-direction and lifelong learning (Figure 6) (ibid., pp. 582-583).

For developing a classification of future skills, the literature review of Van Laar et al. (2017) is useful as it includes skills beyond mere technical use. This corresponds with our findings in the literature that both digital and non-digital (analogue) skills are required in the digital transformation. However, the core skill categories identified by Van Laar et al. (2017) have a strong focus on ICT use. The results of our literature review show that skills such as problem-solving, creativity, critical thinking are needed for the digital transformation but not only when using ICT but also in new organisational settings (such as agile ways of working). Therefore, it seems to be more useful to differentiate digital skills and non-digital (analogue) skills. Another shortcoming of the literature review is its focus on 21^{st}-century skills instead of the full range of skills needed for the digital transformation (incl. T-shaped skills etc.).

Figure 5: Core Skills for the 21st century Knowledge-based economy

Core Skills	Conceptual Definitions
Technical	Skills to use (mobile) devices/applications to accomplish practical tasks
Information management	Skills to use ICT for searching and organizing information
Communication	Skills to use ICT to transmit information
Collaboration	Skills to use ICT to develop a social network and work in a team
Creativity	Skills to use ICT to generate new ideas and transform them into products/services/processes
Critical Thinking	Skills to use ICT to make informed choices
Problem Solving	Skills to use ICT to find a solution to a problem

Source: Adapted from Van Laar et al., 2017, Table 4, p. 583.

Figure 6: Contextual Skills for the 21st century Knowledge-based economy

Contextual Skills	Conceptual Definitions
Ethical Awareness	Skills to behave in a socially responsible way
Cultural Awareness	Skills to show cultural understanding
Flexibility	Skills to adapt thinking to change ICT environments
Self-direction	Skills to set goals and to manage progression
Lifelong Learning	Skills to continually explore new opportunities when using ICT

Source: Adapted from Van Laar et al., 2017, Table 5, p. 583.

Moreover, the study is explicitly restricted to knowledge-workers, so it does not consider the gamut of jobs across the whole economy. Thereby, it is focused on high-skilled workers and excludes low-skilled workers, who are also estimated to become increasingly important (s. polarization scenario). However, professional skills are not included in Van Laar et al.'s framework of 21st-century skills, whereas we consider them to continue to remain important in the digital transformation. Finally, the systematic review of the literature was restricted to peer-reviewed articles. While the methodology seems reasonably scientifically robust, restricting the search to peer-reviewed articles meant that grey literature such as reports published by well-established institutions on skills, such as Cedefop, Eurofound and OECD, were excluded from the search parameters. This concerns, among others, the classification of Eurofound on physical/manual, cognitive and interactive tasks developed by Fernández-Macías et al. (Eurofound, 2016). Due to the focus on knowledge workers, physical/manual tasks are not covered (increasing in sectors such as health care). Bearing in mind the aforementioned limitations, the identified skill categories will be integrated into the BEYOND4.0 framework.

The Task-Based Approach of Eurofound

A serious candidate to serve as a role model for the BEYOND4.0 skills classification is the Eurofound (2016) framework as different institutions and studies use it for estimating future skill demands (Figure 7). It is the basis for the European Jobs Monitor, included in the skills forecast of CEDEFOP and Eurofound (2016), to analyse how tasks (and, by extension, jobs) are likely change in the future. Even if the Eurofound framework is a task-based approach, tasks have also been interpreted as synonymous for skills as done by the McKinsey Global Institute (Bughin, 2018). This report modified Eurofound´s framework, but at its core, it translated tasks into skills. Despite some limitations of the study (s. deliverable 6.2), this classification of skills proved very useful. It has been estimated skill demands in Western Europe and the US and differentiated by sectors in detail.

To describe and analyse what people are doing at work (and how their tasks are changing), Fernández-Macías and his colleagues developed a framework that distinguishes the content of tasks and the methods/tools for performing these tasks (Eurofound, 2016, p. 38).

These two axes include "the ***what*** and ***how*** of work activity" (Eurofound 2016, p. 37). The task content is closely related to economic activities demanded in certain sectors (such as physical tasks in manufacturing, interactive tasks in healthcare, etc.). The methods and tools mean the technologies (ICT and non-ICT) that are used to carry out the task and the organisation in which this is embedded. Using ICT-tools can be used as a proxy for demand for digital skills, while the methods can be understood as indicators for the work organisation in which people are working (and using technologies). Both technology use and work organisation have an impact on tasks and skill needs (as we mention in section 5). Thereby, the Eurofound framework covers both influencing factors of the digital transformation, which is about technologies (CPS, IOT etc.) and interaction of technology and people (mediated by a work organisation).

This framework seems to help classify future skills as foreseen within WP6 of BEYOND4.0 as it includes many categories that cover skill needs we identified within task 6.2 (such as problem-solving, literacy, numeracy, social skills). So, BEYOND4.0 uses the results Cedefop/Eurofound (2016), and Bughin (2018) have elaborated.

However, the classification has to be reworked to cover all the skill categories we identified as relevant in the digital transformation. Furthermore, it seems important to the research team of WP6 to differentiate carefully between tasks and skills. Within BEYOND4.0, we estimate the impact of digitalization on changing tasks and jobs and what skills are needed to perform these changed tasks. The categories used by Eurofound (2016) do not fully cover the needed skills. For instance, professional skills needed to perform tasks are not included in the task-based framework. However, as we found during research within task 6.2 of the BEYOND4.0-project, the combination of professional and digital skills seems to be very important for the digital transformation, at least in some sectors (such as manufacturing or health care). Therefore, we could not estimate relevant skill needs without the category of professional skills.

Furthermore, personal skills such as attitude, values, self-management and flexibility are often mentioned as skills that are increasingly demanded for the digital transformation. The Eurofound framework does not provide for such a category. Another shortcoming from BEYOND4.0-perspective is that "using ICT" does not provide information on which skills are needed; is it basic, moderate or advanced skills? Is it on common computer use (such as MS Office programs) or Industry4.0-technologies?

Due to these limitations of the Eurofound framework regarding the aim of BEYOND4.0 to identify future skill needs for the digital transformation, we have to develop further a framework based on the Eurofound framework but which is better able to incorporate all of the skill categories identified as relevant in literature research and field work of WP4/8.

Figure 7: Eurofound's Classification of tasks according to contents and methods

	Content
1.	**Physical tasks**: Tasks aimed at the physical manipulation and transformation of material things, which can be further differentiated into two categories:
	a. Strength: Tasks that generally require the exertion of energy and strength
	b. Dexterity: Tasks that generally require a fine physical skill and coordination, primarily using hands
2.	**Intellectual tasks**: Tasks aimed at the manipulation and transformation of information and the active resolution of complex problems, which can be further differentiated into two categories:
	a. Information-processing: Manipulation and transformation of codified information, which can further be differentiated into two:
	(i) Literacy: Manipulation and transformation of verbal information

	(ii) Numeracy: Manipulation and transformation of numeric information
	b. Problem-solving: Tasks that involve finding solutions to complex problems, which can be further divided into:
	(i) Information-gathering and evaluation of complex information
	(ii) Creativity and resolution
3.	**Social tasks**: Tasks whose primary aim is the interaction with other people, which can be further differentiated into four subcategories:
	a. Service/attending: Personally serving or attending customers, clients or patients
	b. Teaching/training/coaching: Training and coaching others
	c. Selling/influencing: Persuading and influencing others
	d. Managing/coordinating: Supervising and coordinating others
Methods and Tools	
4.	**Methods**: The forms of work organisation used in performing tasks, which can be further differentiated into three subcategories:
	a. Autonomy: The extent to which the worker is free to carry out the tasks as they need
	b. Teamwork: The extent to which the work is carried out in direct cooperation with a small group of co-workers
	c. Routine: The extent to which the task is routine and standardised
5.	**Tools**: The type of technology used at work, which can be further differentiated into two main types of technology:
	a. Machines (excluding ICT)
	b. Information and communication technologies

Source: Eurofound (2016), Table 2, p. 38.

Developing the BEYOND4.0 Skills Framework

Considering the strengths and weaknesses of the above-described frameworks, BEYOND4.0 has developed its framework, which is based on a literature review (conducted within task 6.1 and 6.2) and at the same time on practical experiences derived from the Blueprint-projects for sectoral skills alliances (such as the European Skills Strategy and Alliances ESSA[4]).

[4] The ESSA project has received funding from the European Union's Erasmus+ programme under agreement No.2018 - 3059 / 001 - 001.

Based on systematic literature, Janis and Alias (2018) identified 52 technical competencies which cover a wider scope than purely digital skills. Their framework includes state of the art knowledge, manufacturing skills, IT skills, computer science and robotics/automation. Computer science and IT are the most mentioned competencies/skills (ibid., p. 1061). Knowledge in IT includes big data analysis and interpretation, IOT application, knowledge on IT security and data protection.

Beyond these technical skills, Janis and Alias (2018) identified 31 non-technical skills which are required for Industry 4.0. The authors mention problem-solving, creativity, decision-making and adaptive skills as the most common non-technical skills. Based on their systematic literature review, Janis and Alias (2018, p. 1065) suggested four main categories of non-technical skills needed for Industry 4.0: the personal, social, professional and methodological skills.

Figure 8: Summary of non-technical competencies and skills of Industry 4.0

	Major Competencies	Type of Non-Technical Competencies and Skills	Scholar
Non-Technical Competencies and Skills	Personal competencies and Skills	Cognitive abilities, Self-awareness, self-regulation, self-organizing, self-discipline, positive work attitude, proactive, ability to learn, ability to adapt	(Büth et al., 2017; George Chryssolouris et al., 2013; Dittrich, 2016; Gronau et al., 2017; Müller-Frommeyer et al., 2017; Prinz et al., 2017)
	Social Competencies and Skills	Ability to work in a team, have good communication skills, and work in an interdisciplinary area.	(Büth et al., 2017; Forfás, 2012; Gehrke & Kühn, 2015; Gronau et al., 2017; Ministry of Indonesia, 2017; Müller-Frommeyer et al., 2017; Prifti et al., 2017)
	Professional Competencies and Skills	Leadership skills, presentation skills, project management skills, business strategy, customer orientation and relationship management, persuasion, coordinate with others, training and teaching others	(Büth et al., 2017; Gronau et al., 2017; Müller-Frommeyer et al., 2017; Chase, 2017)
	Methodological Competencies and Skills	Analytical skills, complexity skills, problem solving skills, planning skills, creativity, decision making.	(Acatech, 2017; Dittrich, 2016; Fantini et al., 2016; Forfás, 2012; Ministry of Indonesia, 2017; Prifti et al., 2017; Richert, et al., 2016)

Source: Janis and Alias (2018), Table 04. p. 1065.

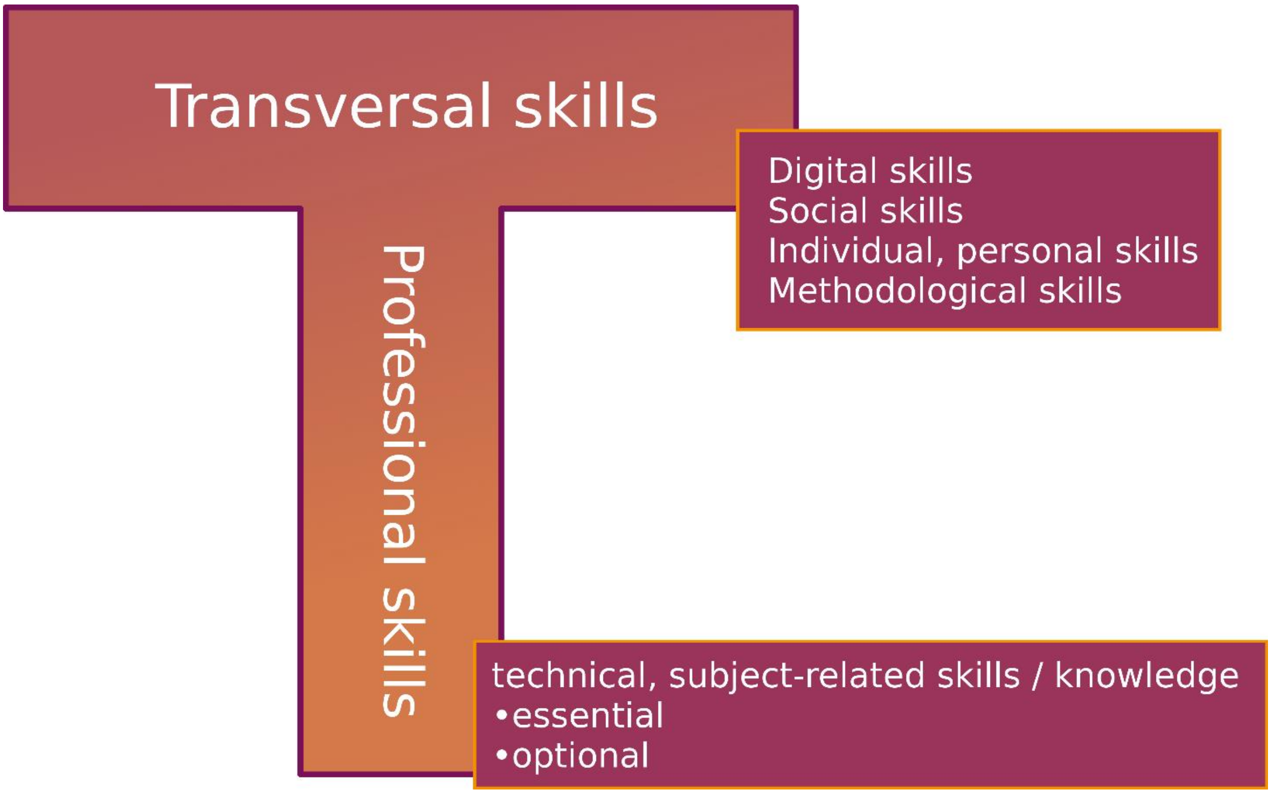
This categorisation is fully in line with categories, BEYOND4.0 identified during research on skill demands for the digital transformation. As mentioned above, professional skills play a vital role despite often neglected in literature due to the myriads of professions (and related professional skills) that can be differentiated (Handel, 2012). However, having a closer look at skill needs on sectoral and company level, a need for interwoven digital and professional skills has become obvious. This will be described in the following paragraphs, which include descriptions of which skill needs are identified on different (EU, international and sectoral) levels.

These findings from the literature review are confirmed by the so-called Blueprint-projects, which represent the skill needs of selected sectors in Europe (such as steel, industrial symbiosis in process industries). These blueprints for developing skills needed due to digitalisation and decarbonisation are part of the *New Skills Agenda for Europe* (European Commission, 2016). As they are driven by industry, they have practical evidence in companies.

The skill classification used in the European Steel Skills Agenda (ESSA) is based on the T-shaped model, as many classifications of skills found in the literature are based on this approach.

The current classification of ESSA takes up very similar skill categories as adopted in the BEYOND4.0-project. Being in use in steel companies, this classification should be very practical (Figure 9). This approach fits the general framework we presented in section 3. It is possible to integrate our more detailed categories into the ESSA categories of skills without losing sight of all relevant skills.

Figure 9: The model of T-shaped skills



Source: ESSA (2020). Blueprint "New Skills Agenda Steel": Industry-driven sustainable European Steel Skills Agenda and Strategy (ESSA) Mid-term Report Deliverable D1.4, 31 December 2020, Figure 12, p. 36.

Professional skills are understood as domain-specific (job-, occupations specific) and include technical subject-related skills. Transversal skills are not limited to a specific job or domain but are generally required in the digital transformation. The professional skills are already taken from the ESCO classification. For the transversal skills, ESCO is currently elaborating an appropriate classification. Transversal skills comprise methodological skills, social skills and individual skills. The categories "complex and creative thinking" are part of methodological skills. Self-management and management skills can be assigned to individual skills. Also, basic skills can be assigned to individual skills and digital skills. The following figure shows how detailed sub-categories could be assigned to the major categories:

Figure 10: Sub-categories of transversal skills

Digital skills	Social skills	Individual, personal skills	Methodological skills
Use of digital devices	Communication	Decision making	Creative problem solving
Cybersecurity	Interdisciplinary exchange	Personal experience	Process analysis
Data analysis and interpretation	Teamwork	Adapt to change	Learning to learn
Use of complex digital communication tools	And so on	Work autonomously	Critical thinking
And so on		And so on	And so on

Source: https://www.estep.eu/assets/Uploads/ESSA-D6.2-Industry-Skills-Requirements-Version-1.pdf

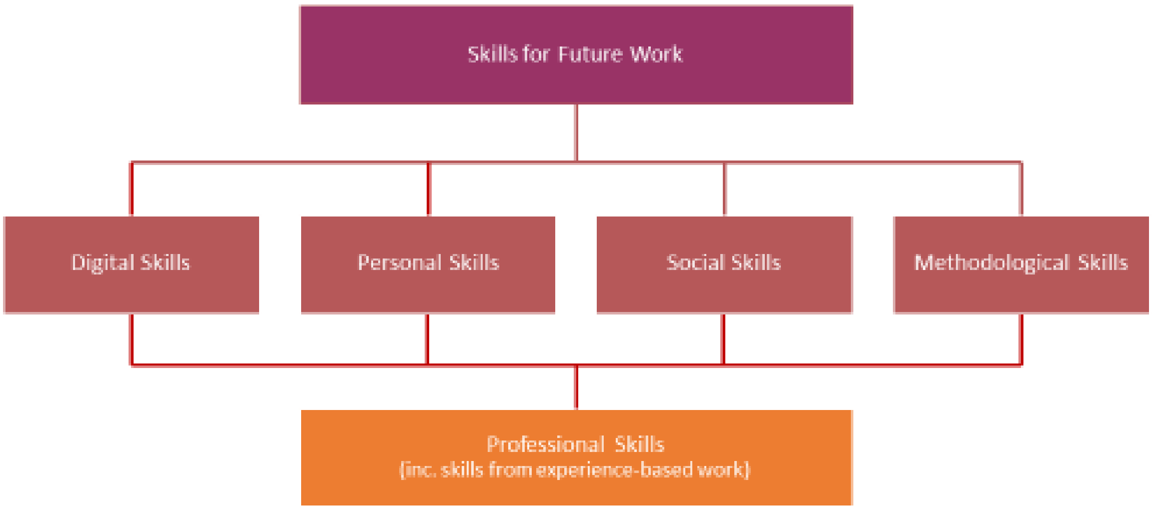
These categories are preliminary because they will be harmonised with ESCO that currently develops a classification for transversal skills. However, ESCO is currently going to assign digital skills to the category of professional skills. The first meeting between ESCO and researchers of the blueprint project took place in November 2019. In BEYOND 4.0, we will compare our approach to ESCO's when they publish the specific new transversal skills operationalisation in the summer of 2021 and decide whether it is useful to our project and can be integrated.

The BEYOND4.0 Classification of Skills

The BEYOND4.0 skills classification is making use of the non-technical skills categories of Janis and Alias (2018), which is also used by blueprint projects such as ESSA. It covers widely the relevant non-technical skills we found in the literature review for task 6.2 – results will be published in deliverable 6.2. Regarding the technical skills, BEYOND4.0 is using categories that are focused on digital skills, which are often differentiated by basic and advanced professional skills, sometimes added by digital skills needed for researching and developing digital technologies.

Figure 11 shows the skills classification BEYOND4.0 is using for analysing skill demands for the digital transformation:

Figure 11: The BEYOND4.0 classification of skills for future work



This categorisation includes professional (job-specific) skills and transversal skills consisting of digital skills and analogue skill: personal skills, social skills and methodological skills. While digital skills are usually understood as transversal skills which could be applied to many jobs, there sometimes is an overlapping of digital and professional skills when digital tools are used explicitly for certain jobs and sectors such as healthcare or IT. The sectoral analysis carried out in task 6.2 shows that there is often an intertwinement of professional skills and digital skills when experienced-based and data-based decisions are made, for example, controlling of installation/plants in manufacturing. Also, links between complex thinking and professional skills can be considered when it comes to optimisation processes that take the owned sub-process and previous and subsequent processes into account. The following section describes the skill categories of the BEYOND4.0 classification of skills for future work:

Professional skills

Professional skills refer to those particular and specific skills to the field of work, domain or occupation in question. They are the counterpart to general skills as they refer to the use of specific knowledge. Given a large number of professions, it is not very feasible to carry out an analysis of the effects of the digital transformation on any profession: "Automation is leading to the transformation of the very nature of a myriad of occupations (Gonzalez Vazquez 2019, p. 29; see also WEF, 2018 and Handel 2012, p. 8). It is therefore not surprising that there are hardly any publications in the literature - at least at EU/OECD level. On a sectoral level, various technical skills are mentioned in the blueprint projects of the sector: DRIVES, the skill strategy blueprint project for the automotive sector, compounds a whole list of skills in increasing demand that we would classify as professional skills: technical knowledge, mechatronics, materials sciences. Pfeiffer et al. (2016), when examining digital transformation and skill changes in the subsector of plant and mechanical engineering, emphasise the importance of experience in a specific domain and work environment to adapt to and cope with change (Pfeiffer et al., 2016, p. 39). One important finding of our literature review is that advanced digital skills go along with professional 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 (Pfeiffer et al., 2016, p. 99).

Digital skills

It can be said that all reviewed studies/surveys on the EU/International level predict increasing demand for technology-related skills - which does not seem very surprising. They differ in whether they see the main future importance in basic or advanced skills. Apart from this distinction of digital skills made in the first report of deliverable 6.1, the EJS survey (Cedefop 2016) introduces another sub-category of digital skills, the moderate skills that entail, e.g. word-processing or creating documents and/or spreadsheets. This sub-category is very helpful as basic skills are not always clearly defined or sometimes only cover basic computer skills such as using a mouse or up-/down scrolling within screens. Cedefop (2016) and Gonzalez Vazquez (2019) stress the importance of moderate digital skills as they are currently required from 52% of employees (in EU28-countries) to do their jobs - followed by basic skills (19%), advanced skills (14%) and no requirement for digital skills (14%). Therefore, the combination of basic and moderate skills currently account for the largest share of the demand for digital skills (needed by seven from 10 adults).

Estimations on relative changes of (basic/advanced) digital skills differ among studies. It cannot be decided yet which level of digital skills (basic or advanced or moderate) might increase more rapidly in demand. This being the case, we can predict with reasonable confidence that jobs that are expected to grow in the future will at least require basic digital skills (Gonzalez Vazquez et al. 2019, p. 6). Based on a survey of executives (mainly HR), Bughin (2018, p. 10) states that "all corporate functions are expected to improve their digital literacy over the next three years" (Bughin, p. 10). So, it can be concluded that there either is or will be a future requirement for digital skills to be improved for employees at all skill levels.

Personal Skills

This skill category is operationalised in different ways by various studies. As described in deliverable 6.1, we understand personal skills are personal traits people require to perform their jobs. Personal skills include self-reflection, learning skills, integrity, responsibility, attitude (individual values/ethics), motivation, and entrepreneurial skills such as readiness to take the initiative and risks (Abel 2018, p. 28). The OECD study Trends in Job Skill Demands (Handel 2012, p. 9) explicitly excludes these skills from its analysis because they consider them "personality and motivational characteristics". Nevertheless, we retain personal skills as an important category within the BEYOND4.0 skills framework, as emphasized by several authors on EU-/OECD-level, especially at a sectoral level.

At an EU/International level, personal skills are usually not considered as an explicit skills category. JRC (Gonzalez Vazquez 2019) and Cedefop/Eurofound (2018) analysed some skills which are assigned to an overarching category called non-cognitive skills. Despite the ambiguous categorisation, personal skills are likely to continue to play an important role in the work of the future. Non-cognitive skills are considered "unique human skills" and, therefore, not likely to be replaced by digital technologies. Based on a study by WEF (2018), emotional intelligence as a personal skill is expected to increase between 2018 and 2022. Cedefop´s OVATE project analysing online job vacancies ranks as the highest the skill "adapt to change" among the most mentioned skills (in more than 21 million job advertisements)".

On a sectoral level, those personal skills, which the Beyond 4.0 project defines as self-management skills and attitude, that have been identified to be increasingly in demand in the considered studies were adaptability (Bughin et al., 2018, p. 32; DRIVES, 2020) and flexibility (DRIVES, 2020), the attitude to be open for new things (Pfeiffer et al., 2016, p. 116) and continuous learning (Bughin et al., 2018, p. 32). All of which seem to point in the same direction of being open and ready for change.

Social skills

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 teamwork 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 of high relevance in the context of digital transformation to be understood as the increasing use of AI/automation on one hand and organisational changes on the other hand (s. WP3, Milestone 4). Bughin (2018) and Cedefop/Eurofound (2018) expect an increasing demand for social skills as they are hard to automate from the technological perspective. From the perspective of work organisation, the OECD (2012) expects an increasing need for social skills and related skill shortages in administration, management knowledge and co-ordination with others, particularly in countries where organisational restructuring has been deeper" (OECD 2017, p. 74).

Bughin (2018, pp. 8-11) identified social skills as the second most needed in the future (after digital skills). Specifically, skills such as leadership and managing people, advanced communication and negotiation and interpersonal skills /empathy are expected to increase until 2030. Task indices based on the European Jobs Monitor show general growth on social tasks, with strong demand for social and selling/persuading skills.

In the OVATE project analysing online job vacancies, social skills comprise three of the top 10 skills, higher in prevalence than any other major skill category. These three social skills received 28.5 million mentions in the online job vacancies analysed, where, for example, team-working was mentioned in more than 13 million job advertisements (Cedefop 2020).

At a sectoral level (e.g. manufacturing), interdisciplinarity (Ergas, L. & Smyrnakis, G., 2020) and interdisciplinary teamwork (Pfeiffer et al., 2016) will be needed in the digital transformation along with specific management and leadership skills (Bughin et al., 2018; DRIVES, 2020).

Methodological skills

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 (s.

Abel 2018, p. 28). 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 (OECD, 2016/2019). Basic skills that are typically acquired in the early years of life through family and primary schooling include basic literacy, numeracy, basic language skills (articulate in one language) and cognitive skills. They form the basis for lifelong learning and have become a minimum requirement for recruitment in Europe.

There is a high level of agreement found within the reviewed studies that *advanced* methodological skills such as problem-solving and creative thinking are increasing importance for future tasks and jobs.

There was less consensus, however, about future requirements for *basic* methodological skills. MGI (Bughin 2018) and WEF (2018) expect demand to decline for basic skills in the future. However, the demand for basic methodological skills appears to be somewhat country-dependent. For example, the OECD (2017) has identified a critical shortage of basic skills in several European countries. Cedefop/Eurofound (2018) predict a moderate growth of (basic) intellectual tasks (numeracy, literacy). However, basic skills are also crucial for individuals, member states, and regions to benefit from the digital transformation. This is due to these skills being essential for employability, and they make an important contribution to the inclusion of people in (digitised) work processes. Additionally, the basic skills are prerequisites for acquiring higher-order cognitive skills, such as analytic reasoning and having access to further job-specific knowledge (OECD 2019).

The increasing demand for methodological skills is related to technological and organisational changes. (Advanced) Methodological skills such as creativity and critical thinking are considered as ´human' skills that are likely to retain or increase in value in digital transformation (WEF 2018, p. 12). A high complementarity exists between planning and basic/moderate digital skills; and between problem-solving and advanced digital skills.

Changed in this update

During the work on task 6.2 on skill demands, we examined the extent to which the skills classification presented in the first report (of deliverable 6.1 in December 2019) was able to cover all of the skill needs identified in the literature (and later on in the fieldwork component conducted as part of work packages 4 and 8). The desk-based research results indicate that the main shape and skill categories have been proven to reflect demands for future skills accurately. The current BEYOND4.0 skills classification represents the T-shaped model, including the specific (= professional) skills and the transversal skills: digital, personal, social and methodological skills (s. figure 9). The sub-categories have been adapted and refined based on the findings of our literature review.

Digital skills

The original sub-categories were basic, advanced digital skills and skills for researching/developing new digital technologies. However, analysis of literature has highlighted that differentiating between advanced digital skills and skills for researching/developing technologies is problematic. One reason for this difficulty in distinguishing between advanced digital skills and skills for researching/developing technologies is because the former sub-category of skills is necessary for the latter sub-category. On the other hand, the European Skills and Jobs Survey (Cedefop 2016) introduced a distinction between basic and moderate digital skills, forming fundamental digital skills. This seems to be a more accurate or meaningful differentiation, as in some sectors (such as wholesale and retail) a shift from basic to moderate digital skills can be observed. The original distinction between basic and advanced digital skills would oversee this change. As a consequence, we now differentiate between basic, moderate and advanced digital skills.

Personal skills

We have kept the sub-categories self-management and attitude. The skills mentioned in figure 10, such as getting things done and adapt to change. The list of personal skills found in the literature is much longer and encompasses further skills such as: learning new things, effective performance, under pressure, entrepreneurship, initiative-taking, show responsibility, work independently, and self-reflection (for further details, see deliverable 6.2).

Social skills

Here, we replaced the examples "interaction with customers and coworkers, supervisors" with main general sub-categories skills for internal and external interactions. Here we assigned the different target groups of people in an organisation who communicate/collaborate with: customers, suppliers, partners, employees, colleagues, and supervisors.

Methodological skills

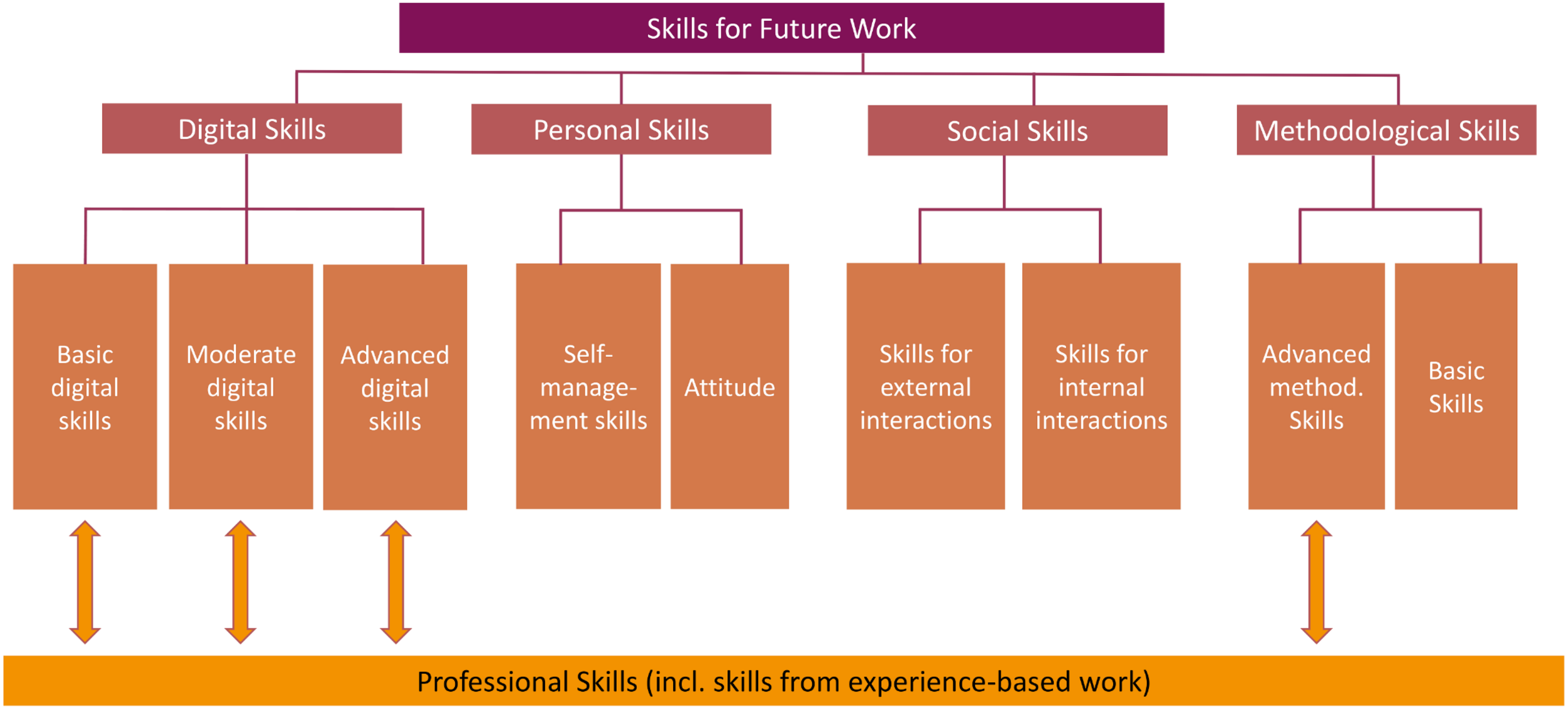
Within this category, we also just changed the terms of the sub-category without changing the actual content of the sub-categories. We now differentiate between basic and advanced methodological skills. The previously named sub-category of problem-solving and creative thinking is not comprehensive enough as there are many more methodological skills mentioned in the literature that are not included, such as find solutions strategies, analytical thinking, critical thinking, complex information processing and interpretation, project management, quantitative /statistical skills and think proactively.

Professional skills

This category remains unchanged.

Figure 12 represents a full classification of skills needed in a digitalized future.

Figure 12: The BEYOND4.0 full classification of skills for future work



5. Quantifying the Changes in Skill Demands (Calculation)

Within the Beyond 4.0 framework, one important perspective is to look at the changes in skill demand in the European Union in terms of proportions and numbers. To enable VET-systems, training providers, policy makers and other stakeholders to better plan training (programmes), there need to be answers to the following questions:

- How does skill demand change because of the digital transformation?
- Do these changes mean that we need to train people in newly emerging skills or are measures of re-skilling and up-skilling indicated to maintain employability?
- Is skills change, which is connected to digital transformation, routine-biased, skill-biased or something else?
- What is the relationship between new technologies and skill demand, and what are the mediating factors?

This framework focusses on changes in skills in digital transformation, whereby the question of changes in employment is only addressed when it affects skill demand. When looking at skills changes on a broader scale, it is helpful to keep in mind that skills are closely connected to tasks: Skills are understood to be necessary for carrying out tasks. Changing tasks call for different skills. As the combination of tasks that form jobs and occupations change over time and through digital transformation, the approach of Beyond 4.0 is rather a task-based than an occupation- or job-based approach.

Changing skill demand and the digital transformation of work

When discussing skills change caused by digital transformation, one important line of argument revolves around automated tasks. An established conceptualisation is that routine tasks are the type of tasks most susceptible to automation (especially by computers) (e.g. Autor et al., 2003). Since the beginning of the 2010s, however, new technology in Machine Learning (ML) has made pattern recognition in big data a new source of potential automation going beyond simple rule-based automation (see section *Skills debate*).

Frey and Osborne (2013) estimated the potential for automation of occupations in the US, looking at the tasks assigned to these occupations in the O*Net database. This is a valuable insight into the potential of ML to take over or change certain tasks. It is noteworthy, though, Frey and Osborne neither predicted how technology would further be developed nor did they say what the automation potential meant for the actual employment structure, occupation and job contents, and ultimately, skills demand. To understand the effects of new technology on skills demand, several other influential factors need to be accounted for, and several arguments have been put forward in response to Frey and Osborne's approach.

For the debate about changes in skill demand, one important shortcoming of Frey and Osborne's perspective is the examination of occupation descriptions. It is well proven that actual jobs differ from occupation descriptions (Crouch, 2005; Pfeiffer, 2016) and that jobs and occupations change and adapt in a dynamic and ongoing manner (Atkinson & Wu, 2017). So, if we assume that certain tasks will be automated, it is probable that the combination of tasks in jobs, and ultimately occupations, will change rather than whole occupations disappear. To observe and especially foresee changes within workplaces, the *within* changes of jobs and occupations might be more insightful than the *in-between* changes. This means that further research needs to include observations from within organisations and jobs for a more accurate analysis of these changes. It is important to understand how tasks change qualitatively and how the combination of tasks within jobs changes when new technologies are introduced. For this, the task-based approach is imperative.

Also, the analysis of the relationship between changes in skill demands and the way organisations are structured and how companies organise work promises valuable insights for our research and has been subject to research before (Ashton, Lloyd, & Warhurst, 2017; Bloom & Reenen, 2010; Borghans & ter Weel, 2006; Felstead & Ashton, 2000; Greenan, 2003). For example, Borghans and ter Weel (2006) were able to show that increased use of information and communication technologies resulted in different impacts in different organisations depending on the organisation's reasons for adopting the technologies and their internal division of labour. Ashton et al. (2017) stress the importance of skill in company strategies and how skill demand changes according to managerial decisions, underpinning the argument Greenan (2003) made with her study, showing that changes in skill requirements and occupational composition of organisations are more closely related to organisational as opposed to technological changes. A study by the CIPD in the UK (Chartered Institute of Personnel and Development [CIPS] & PA Consulting, 2019) differentiated between three types of automation strategies that companies can adopt: the innovation strategy (innovate to stay competitive), the instrumental strategy (case-by-case decisions and short-term perspective) and the absence of strategy, generally not adopting new technologies (Chartered Institute of Personnel and Development & PA Consulting, 2019). They could also show that the implementation of technology is not only dependent on the organisational structure itself but also on which departments get involved and to what extent users get involved in the implementation process, which in turn affects the productivity outcomes (Chartered Institute of Personnel and Development & PA Consulting, 2019). Crouch (2005, pp. 104–105) also stresses that companies may strive to achieve high levels of skills to process them into valuable products or low levels of skills to remain competitive regarding production costs.

Another important question for companies, VET representatives and training providers, policy-makers, and citizens is to know how quickly skill demands change. This means we need to look at the actual technologies being implemented in organisations to assess if and how they are changing workplaces now and in the future. While Frey and Osborne (2013) helped understand the automation potential of ML, a range of other technologies are being implemented in workplaces. We need to look at the different technological trends, their impact and their potential to change work and demand for skills. While some technologies result in the substitution of human labour, others assist us. These assisting technologies can again change the work of human workers with varying impacts, i.e. ranging from rather incremental to disruptive changes.

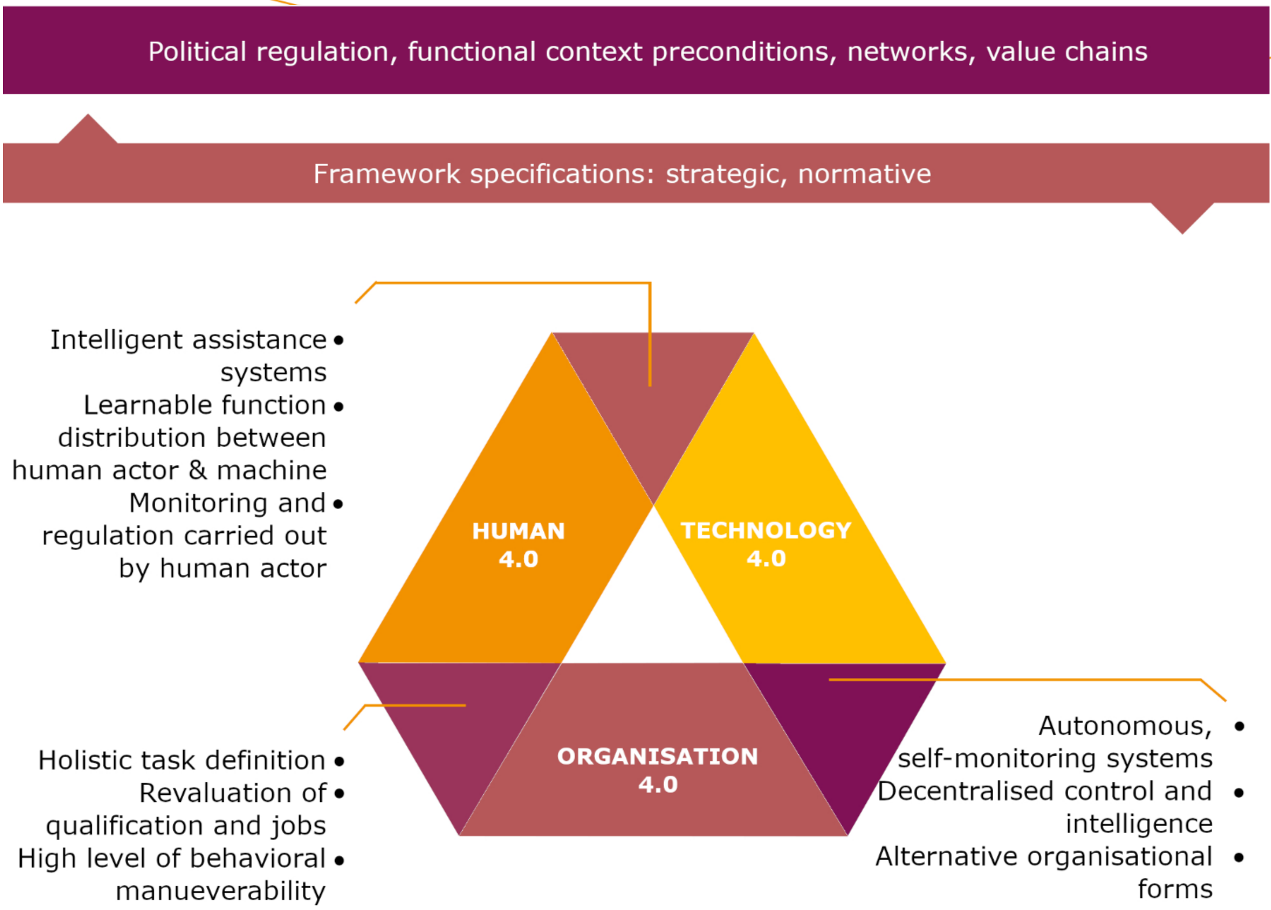
Integrating the organisational level

The literature of the skills debate deals with the connection of new digital technology and resulting skill needs. This perspective easily overlooks the fact that technology and the organisational context have a substantial impact on skill needs (Dhondt, van der Zee et al., 2019). Dhondt and colleagues show that technology is not only an external factor that can be implemented in the firm. The use of technology and management practices are both rather company-specific, aimed at achieving the best possible alignment of technology with the specific requirements of a company. Van Reenen (2011) stresses the influence of managerial practices on raising productivity in this context. This is consistent with the approach of the BEYOND 4.0 project, which is not based on technological determinism, but on the assumption that there is scope for designing technical solutions starting from the organisational needs (Warhurst et al., 2019, pp. 26–27).

This assumption is also consistent with Hirsch-Kreinsen (2016) findings, according to which the design of a technology depends on the composition of development and implementation teams. Experiences in forerunner companies show that the integration of works councils, human resources departments, representative of employees with disabilities significantly influences the implementation process. These groups of stakeholders (can) contribute to an inclusive approach to using digital technologies.

According to the design approach, the same technology can be integrated into different work organisations in very different ways. This is in alignment with the socio-technical system approach (Trist & Bamforth, 1951, which has been customized to Industry 4.0 by Hirsch-Kreinsen, 2016). According to this approach, digital technologies are embedded in an integrated system of the three domains of technology, people and organisation, where a strong emphasis is placed on the three dimensions' interfaces. The *technology-human* interface deals with the division of tasks, functions and decision-making power between humans and machines. At the *organisation-human interface*, the general goals of the organisation, the design of jobs, decisions of work organisation and management strategies are defined. When looking at the *technology-organisation* interface, the focus shifts towards the technological status of the organisation and the organisational use of the existing technology, as well as of planned integration of technology (Abel, 2018, pp. 18–19). Joint optimisation of these three dimensions defines the requirements for skills needed to contribute to that optimisation. In the Beyond 4.0 project, all of these three dimensions shall be considered.

Figure 13: Embedding the organisational context within Industry 4.0- solutions



Source: Dregger, Niehaus, Ittermann, Hirsch-Kreinsen, & Hompel, 2016, Figure 2, n.p.

A recent approach that combines a detailed analysis of the technologies introduced by companies and their organisational setup is TNO's understanding of dominant technology and organisation (Dhondt, van der Zee et al., 2019). This approach considers the concept that (digital) technologies are anything but homogeneous in their effects on organisations and skills. The authors suggest a distinction needs to be made between different technologies and their impact. Identifying the dominant technologies makes it more likely to identify the key impacts of digitalisation. Analogous to the abovementioned design approach, Dhondt, van der Zee et al. (2019) also consider the dominant organisational context as a method to estimate the impact on skills demand.

In respect of the analysis of technologies within organisations, Dhondt and colleagues propose a threefold process: first, specify the focus technologies; second, understand the heterogeneity of technology in the organisation (especially in terms of vintage and new technologies) and, third, actual measurement of technology (Dhondt, van der Zee et al., 2019).

They differentiate between five types of current digital technologies that "have distinct predicted impacts on employment dimensions" (Dhondt, van der Zee et al., 2019, pp. 188): hard automation, human enhancement (supporting) technology, communication technology, information technology and management systems. Apart from their different ways of affecting skill demand in general, the dominance of a particular type of technology can be measured by using an approach that identifies three phases of technologies: the potential phase, the investment phase, and the phase of actual use (i.e. post-implementation). The phases are based on the measurement of the percentage of patents registered in the past five years as compared to the total number of patents in one field of technology (potential), the investments compared to a reference year into development (investment), and the percentage of companies using a technology (actual use) (Dhondt, van der Zee et al., 2019).

To understand the connections between technologies and skills demand, the organisational context needs to be considered. Dhondt and colleagues use a categorisation originally introduced by Lorenz and Valeyre (2005), which distinguishes between four organisational types: learning organisations, lean organisations, Taylorised organisations and simple organisations.

The analyses of Dhondt, van der Zee et al. (2019, pp. 197) of two occupations in the Dutch manufacturing industry show “that communication technology and Taylorisation will be the dominant technology and organisation in the coming years.” Based on these results, the expected impact on skills demand can be specified. Amongst others, decreasing needs for the so-called 21st-century skills are expected. As one effect of the strong diffusion of communication technologies, the authors expect a strengthening of hierarchy and narrowing of tasks. Consequently, skill needs for workers in this kind of digital work environment are predicted to decrease. Whilst rather specific, this methodology and the results it generates serve to illustrate the advantages of the concept of dominant technologies and organisations as a way to estimate the impact of the digital transformation on future skill needs.

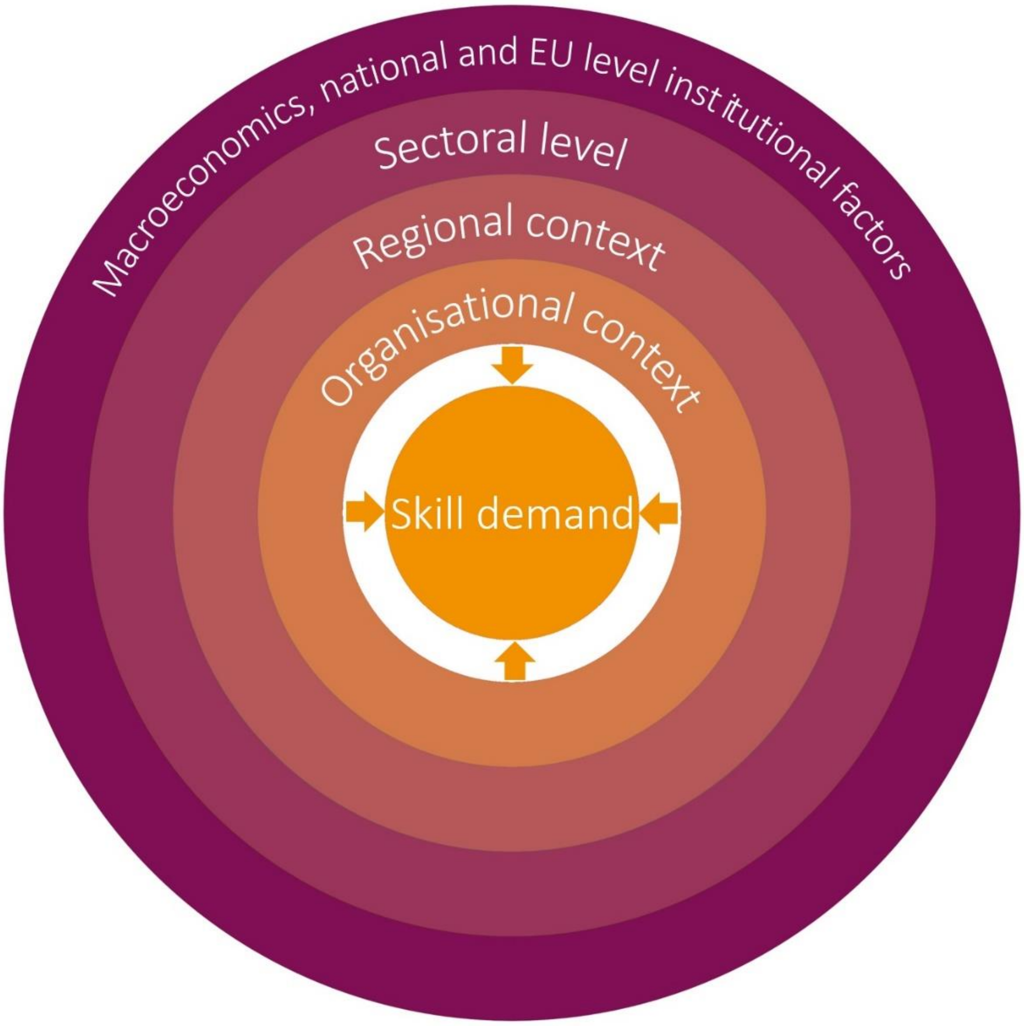
When observing the organisational context, it is important to consider that companies (and often also public service organisations) do not prioritise skill development or even develop organisation-wide skill strategies. Rather, the chain of reasoning is: business development is the most important strategy of companies, which leads to organisational development, which in turn leads to workforce development, including skills (Warhurst, 2014).

Influencing factors on skill demand

To better predict the trajectory of skill demand, it is also necessary to look beyond the complex dynamics within organisations. Several other influences operate on different levels that can either influence organisations' behaviour and have an *indirect* effect on skill demand or have a *direct* influence on skill demand, mainly by influencing the demand for labour in certain industries or occupations.

Based on a literature review, we found a variety of influential factors for changes in skill demand, where we have categorised them according to the immediacy of their impact (Figure 14).

Figure 14: Different levels of influencing factors on skill demand



We identified the organisational context as the sphere with the most immediate influence on skill demand. Here, jobs and their composition of tasks, as well as tasks themselves, are decisively shaped: Organisations' situations and decisions determine what type of technologies get implemented, in what functionalities and in what scope they are used, how production processes and work organisations are designed, but also the timeframe across which the changes take place and the timeframe across which skills need to be adapted. In short, organisations define task and jobs and thereby what skills are required of their workers and how and when they need to change. In the Beyond 4.0 project, the interviews that will be conducted with company representatives will provide valuable insights into the organisational context and their influences on digital transformation (s. WP 8).

However, organisational behaviour is not only determined by the internal logic. It is also influenced by the regional context and sectoral structures and developments. As the debates about economic clusters and ecosystems demonstrate, the regional context and its conditions influence the development and orientation of companies, (higher) education institutions, regional policies and network-building. Therefore, we hypothesise that the regional level is the second most influential level of influence on skill demand. The empirical results of work package 4, where 12 entrepreneurial ecosystems in six regions across Europe will be examined, will provide valuable insights into the relationship between changes in skill demands and regional characteristics. The empirical investigation of work package 3 will also analyse how regions may influence and deal with the digital transformation. In this respect, the research's foci are on changes in skill demand, changing employment and qualification structures, and the distribution of wealth and needs for an inclusive labour market.

The third level of influence is the sectoral one, where dynamics of competition, structural change and sector-wide negotiations of trade unions and employers' associations define trends and set standards for the actors within the sector, including companies and training providers. Finally, institutional configurations also shape the development of skill demand. As regulations, policies and agendas of national and EU institutions set conditions for the sectoral, regional and organisational levels, we consider them to have many mediated effects on skill demand. Following the same logic, we consider macroeconomic factors to have several indirect effects on skill demand by developing EU and national level policy measures, influencing sector growth, regional development, and conditions for organisations. Moreover, more direct influences as the demand for employment, qualifications and certain professions are strongly dependent on macroeconomic developments such as economic growth, especially given the differences between EU member states, sectors and industries.

Regional level

As mentioned, in addition to the organisation level being the most direct sphere of influence on skill demand, we consider the regional level as the next (i.e. second) most influential layer that determines skill demand. From the perspective of the Beyond 4.0 project, regional entrepreneurial ecosystems will be analysed in detail as they form the prerequisites for companies, training providers and VET systems, and policymakers and investors who choose to promote certain industries over others. The dynamics of networks, the collaboration of companies, public authorities and educational organisations can support or hinder industries and the respective companies from growing. Similarly, an ecosystem can influence the digitalisation strategies of companies and, ultimately, the type of change in skill demand. The core elements of an entrepreneurial ecosystem include networks, leadership, finance, talent, knowledge, support services and intermediaries, formal institutions, culture, physical infrastructure, and demand for respective products (Stam, 2015; Stam & van de Ven, 2019). Crouch (2005, p. 103) stresses that communities and local networks may be especially important for skill formation, particularly when small and medium-sized enterprises exist in large number, when new sectors emerge and/or formal institutions are not well trusted.

In the Beyond 4.0 project (Work Package 4, see van der Zee (2019)), we adopt an analytical approach that combines the perspectives of entrepreneurial ecosystems with that of business ecosystems (Tsujimoto, Kajikawa, Tomita, & Matsumoto, 2018). While entrepreneurial ecosystems have a stronger focus on the territorial boundaries of a region, the business ecosystems approach emphasises the networks and interrelations between actors.

Sectoral level

The importance of the sectoral level for changes in skill demand is also stressed in the literature. Firstly, some influences mainly change the labour demand, such as sectoral growth (Cedefop & Eurofound, 2018; Staab & Prediger L.J., 2019), replacement demand (Cedefop & Eurofound, 2018, p. 15) and employment levels (ibid. p. 15), and thus have an indirect effect on skills demand.

Secondly, there are also a number of important differences between sectors in terms of the quality of skill demand change. For example, depending on the dominant method of production, the dominant form of corporations and their size, and the content of work in a respective sector, a range of different types of technologies are or will be used, the speed of digitalisation processes varies and the types of use and types of effects of technologies vary strongly. Moreover, the presence (or absence) and actions of trade unions and industrial and employers' associations may also influence changes in skill demand (Staab & Prediger, 2019).

National level and EU level institutional factors

On the national level, there are institutional configurations that factor into skill demand. These consist of labour market regulations (Fernández-Macías, 2012) and other national policies and specific configurations of the relationship between workers (and their representative bodies such as works councils and trade unions) and employers (and their associations) (Staab & Prediger, 2019).

Labour market regulations set the terms by which employers can hire and attain employees and workers can find jobs. Especially through the influences of labour market regulations on labour costs and the political setting of protection or support for certain jobs or industries, employment and/or occupations (Fernández-Macías, 2012). The same holds for the social partners and their agreements. Especially as European and national trade unions try to fend off job loss and downgrading in the quality of jobs that can be triggered by automation. In addition, as social partners can play a role by promoting ways of using new technologies for assistance and protection and influencing the public strategy towards job creation, training provision and workers' protection (The European Economic and Social Committee [EESC], 2018).

Out of societal, as well as economic, reasons, modern states usually also have an interest in developing the skills of their citizen (Crouch, 2005, p. 98) – and therefore states shape their national VET systems, which may also lead to a certain alignment in skill demands of firms, how Crouch (2005, p. 105) points out.

Analogous to how national policies and institutions shape the conditions for change in skill demand, EU institutions, such as EU-wide labour market policies, and economic and monetary policies, can influence the allocation of jobs to specific industries even occupations across the EU. Furthermore, negotiations between workers' and employers' associations on the EU level influence the conditions in which the digital transformation of work occurs and affect skill demands.

Macroeconomic influences

Apart from institutional configurations, several macroeconomic trends can indirectly influence actual skill demand by influencing the employment demand in different occupations and qualification levels. General economic indicators such as economic growth rates and productivity rates can add valuable information in forecasting change in skill demand. The Skills Forecast developed by CEDEFOP, for example, uses several modules trying to capture relevant factors at the macroeconomic level. One module consists of the E3ME multi-sectoral macroeconomic model, which includes economic activity, working-age population by age and gender, wage rates, labour market participation rates, benefit rates, active labour forces by age and gender and unemployment (Cedefop & Eurofound, 2018, p. 15). A study by Manyika et al. (2017) shows that the state of the labour market is an important factor for the uptake of technology and shifting task compositions of jobs.

One important trend on the macroeconomic level that does not stem directly from digital transformation is offshoring (and in reverse, in-shoring), as Foster-McGregor, Nomaler, and Verspagen (2019) have shown in their study. Additionally, trade and globalisation of markets and, with it, access to external markets (Acemoglu & Autor, 2011; Foster-McGregor et al., 2019) can influence those industries, and in which kind of jobs, more people with particular skillsets will be needed. Also of current relevance, economic crises have a quite large impact on skill demand as such crises affect the employment structure and the relations between different industries (Autor, 2015; Cedefop & Eurofound, 2018; Dachs, 2018; Staab & Prediger, 2019).

Skill demand factors - data availability

As shown, change in skill demand is dependent on a range of complex and often inter-related factors that operate on multiple levels (organisational, sectoral, regional, national and EU- level institutional configurations, macroeconomics). While each of these factors receives attention within the skills debate, the question arises as to how these factors can be measured and how they can be analysed in a holistic approach, including measurement of skills. In the following sub-section, empirical data will be presented for each level of analysis, and it will be assessed to ascertain whether a combined analysis of factors may be possible by drawing on existing empirical this data.

A central part of the relevant data derives from (often representative) surveys, but some additional methodologies were applied as well.

Analysing survey data

As shown above, factors influencing skill demand at the organisational level have straightforward effects as they are connected to many concrete organisational decisions, e.g. concerning technologies, production processes and work organisation. Several large international surveys of employers are particularly suitable to cover these factors: the *Future of Jobs survey* and the *Skills Toward Employment and Productivity (STEP)* survey of the WEF (with the latter also providing questions at the household level), the *Continuing Vocational Training Survey, the Community Innovation Survey* and the questionnaire on *ICT usage and e-commerce in enterprises* of Eurostat as well as the *European Company Survey* of Eurofound. However, the raw data of some surveys like the Future of Jobs Survey and the Manpower talent shortage survey, an employees' survey run by the labour-hire company ManpowerGroup, are not publicly available and cannot be used for detailed analyses.

In these surveys, employers' and partially employees' representatives (such as in the *European Company Survey*) are asked to provide details about their strategies about the adoption of technology and their efforts in VET and organisational practices. The STEP survey also includes an employees' perspective into their data collection. However, to directly check any possible links between the organisation's information and skill demands, skills themselves have to be operationalised in these surveys. This proves to be problematic in part, as several of these surveys, such as the *European Company Survey*, only have very general indicators to measure the broad relationship between skills and organisations rather than the relationship between specific skill categories and organisational factors. An exception is the Continuing Vocational Training Survey (CVTS), which allows analyses of company training strategies and skill demands of companies together.

Figure 15: Surveys on organisational level and contents related to the influencing factors and the skills debate

	Survey of Adult Skills	European Working Conditions Survey (EWCS)	European Skills and Jobs Survey (ESJ)	Future of Jobs Survey	Opinion survey on vocational education and training in Europe	Continuining Vocational training survey (CVTS)	Skills Toward Employment and Productivity (STEP)
Institution	OECD (PIAAC programme)	Eurofound	Cedefop	World Economic Forum	Cedefop	Eurostat	Worldbank
Countries	OECD countries	EU countries	EU countries	No sampling on country level	EU countries	EU countries	17 countries from 4 continents
Target population	Adults, aged between 16 and 65	Employees, at least 15 years old (Bulgaria: 16 years)	Adults, aged between 24 and 65	Largest employers in different industry sectors	Adults, at least 15 years old	Employers / enterprises with at least 10 employees	Urban adults, aged between 15 and 64
Skill perspective	What activities do the respondents have in their work and private life? Direct assessment of literacy, numerical and problem-solving in technology-rich environments	What kind of tasks and possibilities do the respondents have in their daily work?	How do the respondents rate the skill requirements at their workplace as well as – and in relation to – their own skill level?	Skill needs for future work out of an employers' perspective	Which skills did the respondents learn in primary / secondary education?	Which skills are taught in vocational education? / What skills are needed for the company?	What skills do the respondents use in daily life and at work? Direct assessment of literacy skills
Cycle	~ Every 10 years (2011-2018, 2018-2023)	~ Every 5 years (1990/91, 1995/96, 2000, 2005, 2010, 2015)	One edition so far (2014), second edition planned (2020)	Has been executed 2016 and 2018	Just one edition so far (2016)	~ every 5 years (1993, 1999, 2005, 2010, 2015, 2020)	Data collected between 2012 and 2017

Some further surveys capture the employees' perspective (e.g. the *Survey of Adult Skills* of PIAAC or the *European Working Conditions Survey*). As already mentioned in sections 2 and 3, individuals may also have intrinsic motivation and demand for skills to secure their position on the labour market and social and economic prosperity. Although employers more often articulate that skill demand, the connection between individual perspectives and skill demand could be analysed further by using such employee surveys. This particularly applies when the surveys have a comprehensive operationalisation of different specific skills. Furthermore, they contain several additional useful variables, e.g. social-demographic characteristics and the respondent's role at the workplace and in VET, which may be interesting for further analysis. Figure 15 gives an overview of the different surveys and their main characteristics.

Above that, Dhondt, Kraan, and Bal (2019) argue that many surveys based on the British Skill Survey (BSS) like PIAAC (Survey of Adult skills) contain several questions regarding tasks that are more or less connected to organisational factors: Preparation tasks, supportive tasks, and regulating tasks. These tasks are - according to them - dependent on organisational decisions and therefore reflect the organisational context. Here, the understanding of skill demands oscillates: Rather than being only individual properties, skill demands become a "function of the division of tasks".

Connecting information on tasks relating to organisational characteristics to more personal skills, like basic generic skills, connections between individual abilities and organisational factors can eventually be detected. While the approach provides effective use of available data, it also seems to be methodologically problematic to measure organisational level factors only on an individual level. Assuming the dependency of certain skills from work organisation, the survey data still represents individual aspects of work organisation rather than representing organisational conditions. However, organisational level data might be included in these statistical calculations (see sub-section two of this chapter) to validate correlations further.

It is also important to cast a light on the operationalisation of skills. At PIAAC, skills are operationalised as actual tasks in jobs, making it possible to integrate the organisational level. The *European Working Conditions Survey* (EWCS) of Eurofound adapts a similar perspective on skills. Still, Cedefop's *Opinion Survey on Vocational Education and Training* and the *Continuing Vocational Training Survey* (CVTS) of Eurostat are looking at acquired/taught skills in education on the individual level, with the CVTS also measuring skill demand more directly by asking the employers which skills they assume to be the most important in the following years. *The European Skills and Jobs Surveys* (ESJ) asks employees for required skills at the workplace. Also, the surveys do not use the same approach to skill categories. A comprehensive overview of how the different surveys can measure skills categories described in the BEYOND 4.0 concept (see figure 10) can be found in Figure 16. It is an excerpt of questions of the respective survey, which provide information on the skills categories. A complete assignment of survey questions to skill categories can be found in the appendix (Survey overview).

Like the assumed impact of ecosystems, factors on the regional level are also anchored in organisational contexts. Although the mentioned surveys contain organisational characteristics, they fail to capture organisations' relations in a particular environment. To gain insights into these effects on skill demand, qualitative research seems to be a promising approach. In this way, for example, the following questions can be investigated:

- To what extent can organisations that are part of such regional ecosystems be influenced by the strategies of other members?
- Do they cooperate to make VET more effective?
- What is the future potential of such cooperation?

A more in-depth look seems to be necessary to answer these questions.

Another interesting source of insights is Skills-OVATE (Skills – Online Vacancy Analysis tool for Europe), a Big Data analysis of online job vacancies and the skills mentioned there, whose preliminary results are available as an interactive online tool[5] (Cedefop, 2019b). As of January 2021, more than 100 million ads from 28 countries (EU countries plus UK) from July 2018 to September 2020 were included in the results, while an expanded version will be released in early 2021 (Cedefop, 2019b). For the analysis, the job vacancies presented or linked on several online job vacancy portals were collected by using various methods: by scraping (if the structure of the website was known before), by crawling (if the structure was unknown and targeted access was not possible) or by direct assessment of the databases based on an API (if the website operator agreed) (Cedefop, 2019a, p. 20). After several data cleaning measures (e.g. deleting duplicates, see Cedefop, 2019a, p. 20), the information in the job vacancies was classified by keyword search and methods of machine learning (Cedefop, 2019a, p. 23). The Skills-OVATE dataset contains information on occupations (based on the ISCO classification), on countries and regions (of the place of work), the demanded skills (based on the ESCO classification), time as well as some other variables, e.g. wages and sectors (Cedefop, 2019a, pp. 26–27).

When interpreting the Skills-OVATE data, some limitations should be taken into account. On the one hand, those responsible referred to problems of representativeness: Not all job vacancies are placed on online job portals, and this proportion may vary by country, qualification or occupation (Cedefop, 2019a, p. 24). Another strand of reliability limitations concerns errors that occur in the course of automated data classification (Cedefop, 2019a, p. 24): The used algorithms cannot correctly record unusual formulations or certain contexts of meaning. When interpreting the data, further non-methodological limitations should be considered: The vacancies do not necessarily reflect the actual skill requirements for a particular job in an organisation. Instead, it should be seen as an external communication of the organisation, by which certain required skills could be left out, and other skills could be emphasised. Besides, skill needs that are met within the organisation (e.g. by training of employees) are generally not communicated in job vacancies.

The possibilities to combine the skills related data with some further characteristics, like sectors or occupations, which may explain some of the skill demands, are restricted to data visualisation options the Skills OVATE website provides, which, however, may improve after the update announced for early 2021.

[5] https://www.cedefop.europa.eu/en/data-visualisations/skills-online-vacancies

Figure 16: Questions in surveys capable of measuring skills[6]

Survey	Question	Digital skills	Personal skills	Social skills	Methodological skills	Professional skills
European Working Conditions Survey (EWCS) Source: Source questionnaire 6th EWCS 2015)	"[...] does your [main paid] job involve...?" [Q30 / Q49]	"Working with computers, laptops, smartphones etc."	"Being in situations that are emotionally disturbing for you"	"Handling angry clients, customers, patients, pupils etc." [...]		
	"Does your [work / [main paid] job] involve ________" [Q34 / Q48 / Q53 / Q55]		"assessing yourself the quality of your own work" "learning new things"	"visiting customers, patients, clients or working at their premises or in their home?" [...]	"solving unforeseen problems on your own" "complex tasks"	
	[...]					
European skills & jobs survey (ESJ) Source: Final Questionnaire – Cedefop European Skills and Jobs Survey	"[...] how important are the following for doing your job?" [Q22A / Q23A]	"ICT skills" "Technical skills"	"Learning skills"	"Communication skills" "Team-working skills" [...]	"literacy skills" "numeracy skills" [...]	
	"How would you best describe your skills in	"ICT skills" "Technical skills"	"Learning skills"	"Communication skills"	"literacy skills"	

[6] For reason of space, this table is limited to a number of questions and surveys. A full list with all surveys and all questions is set out in Appendix C.

	relation to what is required to do your job?" [Q22B / Q23B]			"Team-working skills" [...]	"numeracy skills" [...]	
	[...]					
Continuing Vocational Training Survey (CVTS) Source: [CVTS 6 manual – Version 1.1 (12 September 2019)]	"In your enterprise, which skills/competences are generally considered as most important for the development of the enterprise in the next few years? [...]" [A12]	"General IT skills" "IT professional skills"		"Team working skills" "Costumer handling skills" [...]	"Management skills" "Problem solving skills" [...]	"Technical, practical or job-specific skills" [...]
	"In 2020, which skills/competences targeted by CVT courses were the most important ones in terms of training hours? [...]" [C5]	"General IT skills" "IT professional skills"		"Team working skills" "Costumer handling skills" [...]	"Management skills" "Problem solving skills" [...]	"Technical, practical or job-specific skills" "Other skills not listed above"
Opinion survey on vocational education and training in Europe Source: [Cedefop European public opinion survey on vocational education and training]	"Would you say that you develop the following skills at upper secondary education?" [Q14a]	"Science and technology skills" "Digital and computer skills"	"The ability to be creative" "Sense of initiative and entrepreneurship" [...]	"Communication skills (M)" "Speaking a foreign language (M)" [...]	"Mathematical skills" "The ability to think critically" [...]	

Multi-level analysis

All in all, possibilities appear to be existing to allow investigation of the connections between skill demand, organisations and individuals by using existing survey materials, at the very least to investigation general interrelations. However, it is not possible to investigate further relevant factors not immediately connected to skill-related decisions, such as factors of national or international institutional configurations and macroeconomic factors, because relevant indicators are not currently operationalised in the existing surveys. This is not surprising because representatives of companies and employees are not always the appropriate experts to answer questions on these topics. To get such information, analyses of other types of surveys/data are necessary.

One example of an investigation predominately relying on macro-level statistics is the skill forecasting work of Cedefop and Eurofound (2018). They developed a modular approach integrating factors for skill demand and supply, as well as imbalances between those factors (Cedefop & Eurofound, 2018, p. 13). To do so, they have analysed data from Eurostat and the European Labour Force Survey (EU-LFS) (ibid.).

The approach of skill forecasting is certainly broad. Skill forecasters are not only considering macroeconomic factors, like labour demand, wage rates and unemployment by different industry sectors and sociodemographic statistics - they also include statistics on formal education (ISCED levels) and actual tasks in jobs. The report from Cedefop and Eurofound (2018) shows how different statistics at the macro level may be used to calculate changes in skills, demand, and supply. For example, statistics on formal qualification are used to forecast the development of skills supply, while the demand for formal qualifications is measured via employment statistics (Cedefop & Eurofound, 2018, pp. 62–76). Changes in occupational employment are also used to verify the commonly cited predictions around the polarisation of jobs (Cedefop & Eurofound, 2018, p. 60).

Concerning specific industrial sectors, there are several reasonably specific reports on the developments of skills demand, e.g. Spöttl et al. (2016) for the metal and electrical industry in Bavaria or Neef, Hirzel, and Arens (2018) for the European steel industry. In these types of studies, specific industrial sectors are analysed with measures of surveys and qualitative interviews. Often, a unique methodology and operationalisation are applied, making it difficult to compare results. However, the aforementioned data sources, survey material and macroeconomic data also allow some degree of differentiation by the industrial sector and may be useful in explaining sectoral trends.

Generally speaking, it is challenging to develop a holistic approach that enables integrating factors that operate at the various levels. For example, the skills forecast framework of Cedefop and Eurofound (2018, p. 15) indicates that there may be several interconnections and dependencies between a number of different levels. However, these interconnections are often only shown argumentatively but not in the actual calculations. Frey and Osborne (2013) fail to integrate organisational and social factors into their approach along similar lines. Alternatively, data focused on the perspective of individuals in organisational contexts fail to consider factors that are distant from the awareness of these individuals.

Figure 17 shows the links between the employee-focused surveys and factors on different levels of analysis (Survey of Adult Skills PIAAC, EWCS, ESJ, Opinion Survey on vocational education and training in Europe). An example for a possible integration of supplementary data would be national institutional configurations: Information on VET systems in different countries could be operationalised, e.g. in the form of a typology, to study the dependency of skill demand on certain characteristics of the VET system.

Figure 17: Survey contents related to the influencing factors and the skills debate

	Organisational context	Regional context	Sectoral context	National context
Survey of Adult Skills (PIAAC)	Number of people working for employer Increase / Decrease of people at workplace Description of business / industry / service (open answers)	-	Sector of employer	Country of residence Country of graduation Country of birth Immigration history
EWCS	Main activity of company (open answers) Number of people working at workplace / employer Tasks and possibilities of workers in daily work	Region	Sector of employer	Country of residence Country of birth Country of birth parent
ESJ	Activities at workplace Number of people working at workplace Skill requirements at workplace	-	Sector of employer Kind of profession	Country of residence
Opinion Survey on vocational education and training in Europe	-	-	-	Country of residence

To combine different levels of insight, a statistical analysis over multiple levels seems to be possible (see also Dhondt, Kraan et al., 2019). For this, the mentioned surveys could be used as a starting point to connect data from the described levels of analysis with data on other levels of aggregation and sampling (cf. Snijders, 2011).

Requirements for better data

As shown before, the surveys were undertaken by large supranational organisations, such as OECD, Eurofound, or Cedefop, allow the analysis of explanatory factors for skill demand. However, there remain barriers to adopting a holistic approach covering the above-mentioned multiple factors and levels of analysis. Existing surveys usually cover a broad range of topics. They, therefore, do not provide the requisite variables to operationalise, in sufficient detail, the wide range of topics relevant to the skills debate. Additionally, surveys do not cover multiple perspectives. This means that it is necessary to draw data from multiple surveys and other databases to conduct additional research, e.g. multi-level analysis or qualitative mixed methods research designs.

As the question of skills demand is among the key questions for digitalisation and automation in working environments, better coverage of actual or projected skills and potential factors influencing skill demand would be useful to track changes and encourage further investigations. In this way, the introduction of new technologies, which potentially has strong social implications, could be accompanied scientifically in a better way.

At the beginning of section 5, we formulated questions of interest concerned with the relationship between the diffusion of new technology / the digital transformation and skills demand. We connected questions to some of the skills debate's central topics, namely how and why the skills demand changes and what these changes mean for the training of the European workforce (up-skilling or re-skilling).

The survey data allow researchers to answer these or similar questions, but only in bespoke contexts: the surveys convey either an employers' or an employees' perspective. They also operationalise skills demand and influencing factors each in a specific way. However, several elements would improve the data available to analyse the changes in skills demand:

- Providing links to other levels of analysis
  Surveys usually cover the individual and organisational levels of the skills situation. To include factors operating at the national or regional level, it would be beneficial to have better links to include data covering these factors. E.g. often, the data cannot be disaggregated to the level of a specific region (i.e. on lower levels than the member state level).
- Combine different perspectives on skills
  We found the surveys we reviewed often had unique approaches to skills operationalisation. For example, some surveys asked questions about the skills the respondents had acquired in formal education; others asked for the skills requirements on-the-job while others probed respondents about skill levels about the skills requirements. In employers' surveys, both skill needs for future work and skills taught in VET are typically included. All of these perspectives are relevant and have each their significance. Nevertheless, it would be insightful to be able to combine some of these different perspectives to gain a more differentiated understanding of this important, complex and multi-faceted topic.
- Standardise skill categories
  While some surveys did not differentiate between different skills, most surveys did, however, they adopted very different terminology. For example, digital skills were sometimes

called "ICT skills" (European skills and jobs survey), "Working with computers [...]" (EWCS) or "Science and technology skills" (Opinion survey on vocational education and training in Europe). Harmonisation of terminology would improve the comparability of findings from across the various surveys. The comparability of the data in terms of the operationalisation of specific skills would be improved if the respective surveys followed the European classification of Skills (ESCO), competences, qualifications and occupations. Among the benefits of adopting the approach specified in ESCO is that it is compatible with the Occupational Information Network (O*Net) framework, which is, for example, used in the Future of Jobs Survey: a conversion of O*Net into ESCO has been done by the Warwick Institute for Employment Research (unpublished).

6. Conclusion and outlook

This deliverable provides information on state of the art related to the skills topics in the scope of BEYOND 4.0. This document highlights several limitations associated with the current conceptualisation of skills. In doing so, it points to the need for enriching the current debate around skills in the context of digitalisation and the future of work. As the second of three reports in the series, it will be further updated in month 38. The subsequent updates will consider additional data that will be fed into WP6 from WP3, 4 and 8. Furthermore, the results of discussions with other work package representatives should be considered as far as (preliminary) results are available. As a result, future reports will also include updates on the concepts to potentially overcome existing limitations.

Enriching the skills debate requires an emphasis on skills needs that enable or support inclusiveness. The current debate about the impact of digitalisation on jobs and skills often revolves around the number of occupations and jobs susceptible to automation, as initiated by Frey and Osborne (2013). In contrast, Atkinson and Wu (2017) use the occupational churn approach that balances the numbers of threatened jobs and jobs that will be emerging due to digitalisation. However, it should be stressed that the skills requirements of emerging jobs will, in most cases, be quite different from those jobs that will disappear. Consequently, there will be a need for closing the emerging skills gap via education and training. Besides, there might be a need for identifying other ways of inclusion for the people who formerly worked in jobs that have been destroyed.

To prevent certain groups of people from becoming losers due to digitalisation, and thereby to ensure inclusiveness, the training of additional skills is needed. Enriching the skills debate requires identifying the gap and the numbers of affected workers to prepare the EU, member states (VET systems), companies and individual EU citizens for those changes.

Another critical issue is to enrich the skills debate around polarisation and upgrading. Many studies revolve around developments in different EU states and different decades. It remains difficult, however, to predict those trends that can be expected in the future. Nevertheless, such estimates remain important to identify groups of employees (and unemployed people) who are most at risk so that preparations can be made to prepare them for the digital transformation by means including up-skilling and re-skilling. Finally, further data from companies and regional ecosystems need to be considered so that estimations, albeit approximate, can be calculated. Furthermore, the potential impact of trends such as platform work has to be considered so that it is possible to gain a better understanding of the potential impact of new forms of work on skill needs.

In particular, the distinction between routine and non-routine activities must be defined more clearly. In the current debate, circular arguments often have been used: routine activities are defined as such that can be automated. Afterwards, it is stated that routine tasks are susceptible to automation. This problem of circular reasoning is exacerbated further by the technology of artificial intelligence (AI). Frey and Osborne (2013) state that this technology can even automate non-routine tasks. However, facing the argument that an activity that can be automated is defined as a routine task, the statement of Frey/Osborne would be impossible. That shows an urgent need for a clear distinction between routine tasks and non-routine tasks, which will also enrich the skills debate in the further course of the project.

The so-called bottlenecks of automation also indicate that routine tasks are not susceptible to automation if they require special dexterity. It must, therefore, be carefully studied what jobs it is possible to automate and those not. Again, the distinction between routine and non-routine tasks is not sufficient. This argument has been confirmed by studies (Pfeiffer et al., 2016; Pfeiffer, 2016; Pfeiffer & Suphan, 2015c) which show that activities that are apparently routine tasks require experience-based skills.

This being so, enrichment of the skills debate requires a more careful examination of which skills are needed in the digital future and which skills are likely to become obsolete. The distinction between routine tasks and non-routine tasks is no longer sufficient to help understand, measure and explain the impact of digitalisation on work.

This deliverable sets out a general framework developed to integrate all of the skills-related issues that will be dealt with in the project BEYOND 4.0. The framework takes account of the requirements of both employers and individuals. In the face of changing labour market structures, it is not only the responsibility of the state and the companies to provide the skills that are needed for the digital transformation. A degree of responsibility also rests with individuals to work towards acquiring the right set of skills for them to remain employable in a changing work environment. This is especially important for the platform economy, where people are and increasingly will be personally responsible for having the right skills to meet customers' demands. Further research within the project BEYOND 4.0 should include the investigation of the question of which skills are needed by people working in the platform economy and how they might acquire those skills.

Conceptualisation, as one building block of the general framework, has been undertaken by developing a preliminary classification of new or increasingly important skills for the digital transformation. A common understanding of skills categories has to be agreed upon with the other work packages. The plan is to validate the classification by integrating data from the research activities undertaken as part of WP3, 4 and 8. Further developments of current frameworks (e.g. Agoria digital skills model or 21st-century skills classification) could be considered in the next iteration of this report. Above all, it will remain important to continue to monitor further developments about the skills classification of ESCO. This is because ESCO's skills classification seems to best capture most of the categories of skills identified in the literature. We will also have to decide whether the operationalisation of transversal skills is done to make it applicable to BEYOND 4.0. Particularly, ESCO´s understanding of digital skills (in a strictly technical sense) must be critically reviewed. Crucially, there remains scope for further adaptation of the preliminary classification of future skills.

The elaboration of the building block calculation of the general framework is based on the analysis of the current skills debate and further literature that examines how and why skills demand changes. Four levels of influential factors have been identified: the organisational level, the regional level, the sectoral context, and the institutional configurations and macroeconomic influences. Adopting this approach, the underlying assumption is that the organisational level has the most direct influence on skills demand changes. The regional context has the second most direct influence, and sectoral and institutional influences on the national or international level have rather mediated, or indirect influence on the skills demand. The macroeconomic influences have both direct and indirect influences on skills demand.

To use this approach for empirical research, several European surveys and databases are available. There are surveys conducted on the individual employees' level containing variables measuring skills with workplace and socio-demographic characteristics. Most of them do not measure organisational characteristics despite them having been identified in theories as being important. In contrast, a number of employers' surveys do include organisational variables and technological uptake. The difficulty is bringing these datasets together. For this to happen, better links between these datasets are needed. The same holds true for connecting these datasets with information about institutional configurations or macroeconomic statistics. During the project period, we will further look into European data that deal with skills and the identified influential factors and will also integrate the findings arising from WP6 and WP3 to provide a comprehensive overview and critical evaluation of the available data.

For a skills debate that includes the discussion of reasons for labour market polarisation (and to a lesser extent upgrading and downgrading), from our point of view, a task-based approach will improve the understanding of the impacts of the digital transformation and facilitate more appropriate expectations of future changes of work and skills demand. This task-based approach includes factors influential at the organisational level. It also examines the actual technologies and use of technologies within organisations and industries. In our next updates of this deliverable, the aim is to further elaborate in what way such an approach needs to be designed and conceptualised. Furthermore, the work and results of the other work packages in Beyond 4.0 are to be integrated to find the adequate framework to analyse and predict the changes in skill demand caused by the digital transformation.

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Appendix A: DigComp framework

Digital Skills Toolkit (itu.int)

Digital Competence Framework for Citizens (DigComp): Competence Areas DigComp features five competency areas. Each area contains a number of specific competencies, proficiency levels, the knowledge, skills and attitudes associated with each competency.

1. Information and data literacy

    1.1. Browsing, searching and filtering data, information and digital content

    1.2. Evaluating data, information and digital content

    1.3. Managing data, information and digital content

2. Communication and collaboration: interacting through digital technologies

    2.1. Sharing through digital technologies

    2.2. Engaging in citizenship through digital technologies

    2.3. Collaborating through digital technologies

    2.4. Netiquette

    2.5. Managing digital identity

3. Digital content creation

    3.1. Developing digital content

    3.2. Integrating and re-elaborating digital content

    3.3. Copyright and licenses

    3.4.Programming

4. Safety

    4.1. Protecting devices

    4.2. Protecting personal data and privacy

    4.3. Protecting health and well-being

    4.4. Protecting the environment

5. Problem solving

    5.1. Solving technical problems

    5.2. Identifying needs and technological responses

    5.3. Creatively using digital technologies

    5.4. Identifying digital competency gaps

Source: DigComp 2.0: The Digital Competence Framework for Citizens. https://ec.europa.eu/jrc/en/digcomp/digital-competence-framework

Appendix B: European e-competences framework (ecF)

EQF Levels	EQF Level descriptions	e-CF Levels	e-CF Levels descriptions	Typical tasks	Complexity	Autonomy	Behaviour
8	Knowledge at the most advanced frontier, the most advanced and specialised skills and techniques to solve critical problems in research and/or innovation, demonstrating substantial authority, innovation, autonomy, scholarly or professional integrity.	e-5	**Principal** Overall accountability and responsibility recognised inside and outside the organisation for innovative solutions and for shaping the future using outstanding leading edge thinking and knowledge.	IS strategy or programme management	Unpredictable–unstructured	Demonstrates substantial leadership and independence in contexts which are novel requiring the solving of issues that involve many interacting factors.	Conceiving, transforming, innovating, finding creative solutions by application of a wide range of technical and/or management principles.
7	Highly specialised knowledge, some of which is at the forefront of knowledge in a field of work or study, as the basis for original thinking, critical awareness of knowledge issues in a field and at the interface between different fields, specialised problem-solving skills in research and/or innovation to develop new knowledge and procedures and to integrate knowledge from different fields, managing and transforming work or study contexts that are complex, unpredictable and require new strategic approaches, taking responsibility for contributing to professional knowledge and practice and/or for reviewing the strategic performance of teams.	e-4	**Lead Professional / Senior Manager** Extensive scope of responsibilities deploying specialised integration capability in complex environments; full responsibility for strategic development of staff working in unfamiliar and unpredictable situations.	IS strategy/ holistic solutions		Demonstrates leadership and innovation in unfamiliar, complex and unpredictable environments. Addresses issues involving many interacting factors.	
6	Advanced knowledge of a field of work or study, involving a critical understanding of theories and principles, advanced skills, demonstrating mastery and innovation in solving complex and unpredictable problems in a specialised field of work or study, management of complex technical or professional activities or projects, taking responsibility for decision-making in unpredictable work or study contexts, for continuing personal and group professional development.	e-3	**Senior Professional / Manager** Respected for innovative methods and use of initiative in specific technical or business areas; providing leadership and taking responsibility for team performances and development in unpredictable environments.	Consulting	Structured – unpredictable	Works independently to resolve interactive problems and addresses complex issues. Has a positive effect on team performance.	Planning, making decisions, supervising, building teams, forming people, reviewing performances, finding creative solutions by application of specific technical or business knowledge/skills.
5	Comprehensive, specialised, factual and theoretical knowledge within a field of work or study and an awareness of the boundaries of that knowledge, expertise in a comprehensive range of cognitive and practical skills in developing creative solutions to abstract problems, management and supervision in contexts	e-2	**Professional** Operates with capability and independence in specified boundaries and may supervise others in this	Concepts / Basic principles		Works under general guidance in an environment where unpredictable change Occurs. Independently resolves interactive issues that arise from project activities.	Designing, managing, surveying, monitoring, evaluating, improving, finding non-standard solutions.

	where there is unpredictable change, reviewing and developing performance of self and others.		environment; conceptual and abstract model building using creative thinking; uses theoretical knowledge and practical skills to solve complex problems within a predictable and sometimes unpredictable context.				Scheduling, organising, integrating, finding standard solutions, interacting, communicating, working in team.
4	Factual and theoretical knowledge in broad contexts within a field of work or study, expertise in a range of cognitive and practical skills in generating solutions to specific problems in a field of work or study, self-management within the guidelines of work or study contexts that are usually predictable, but are subject to change, supervising the routine work of others, taking some responsibility for the evaluation and improvement of work or study activities.						
3	Knowledge of facts, principles, processes and general concepts, in a field of work or study, a range of cognitive and practical skills in accomplishing tasks. Problem solving with basic methods, tools, materials and information, responsibility for completion of tasks in work or study, adapting own behaviour to circumstances in solving problems.	e-1	**Associate** Able to apply knowledge and skills to solve straight-forward problems; responsible for own actions; operating in a stable environment.	Support / Service	Structured – predictable	Demonstrates limited independence where contexts are generally stable with few variable factors.	Applying, adapting, developing, deploying, maintaining, repairing, finding basic-simple solutions.

Note: Beside of concepts explicityly elaborated for the European e-Competence Framework, the table contains description elements of 1) the European Qualifications Framework for Lifelong Learning (EQF), April 2008 and 2) The PROCOM Framework, of which generic job titles were reproduced in original report with permissio of e-Skills UK.
Source: CEN (2014). European e-Competence Framework 3.0: A common European Framework for ICT Professionals in all industry sectors (2014) . European e-CF and EQF level table, Annex 2, page 51.

Appendix C: Survey overview

Suvey	Question	Digital skills	Personal skills	Social skills	Methodological skills	Professional skills
European Working Conditions Survey (EWCS)[7][8]	**“[…] does your [main paid] job involve…?”** [Q30 / Q49] *1: All of the time* *2: Almost all of the time* *3: Around ¾ of the time* *4: Around half of the time* *5: Around ¼ of the time* *6: Almost never* *7: Never*	“Working with computers, laptops, smartphones etc.”	“Being in situations that are emotionally disturbing for you” “working at very high speed” “working to tight deadlines”	“Dealing directly with people who are not employees at your workplace such as customers, passengers, pupils, patients, etc.” “Handling angry clients, customers, patients, pupils etc.”		
	“Does your [work / [main paid] job] involve _______” [Q34 / Q48 / Q53 / Q55] *1: Yes* *2: No*		“assessing yourself the quality of your own work” “learning new things”	“visiting customers, patients, clients or working at their premises or in their home?” “rotating tasks between yourself and colleagues” [Q56 / Q57: Additional questions]	“solving unforeseen problems on your own” “complex tasks”	
			“your order of tasks”			

[7] In EWCS, skills are not directly measured, but tasks in the daily work. Some of the tasks may be used as proxies for skill demand at work, others seem not to be suitable to be interpreted as skill demand. In this overview, only the first ones are included.
[8] Source: Source questionnaire 6th EWCS 2015 (https://www.eurofound.europa.eu/sites/default/files/page/field_ef_documents/6th_ewcs_2015_final_source_master_questionnaire.pdf)

	"Are you able to choose or change…" [Q54] *1: Yes* *2: No*		"your methods of work" "your speed or rate of work"			
	"Do you […]" [Q58] *1: Yes* *2: No*			"[…] work in a group or team that has common tasks and can plan its work?" [Q59 / Q60: additional questions]		
European skills & jobs survey (ESJ)[9]	**"Which of the following describes best the highest level of ____________ required for doing your job?"** [Q21A / Q21B / Q21C] *1: Basic _____* *2: Advanced _____* *3: _______ are not required*	"Information Communication Technology skills"			"literacy skills" "numeracy skills"	

[9] Source: Final Questionnaire – Cedefop European Skills and Jobs Survey (https://www.cedefop.europa.eu/files/2015-10-06_cedefop_european_skills_survey-questionnaire.pdf)

	"[…] how important are the following for doing your job?" [Q22A / Q23A] *0: 0 Not at all important* *1-4: 1-4* *5: 5 Moderately important* *6-9: 6-9* *10: 10 Essential*	"ICT skills" "Technical skills"	"Learning skills"	"Communication skills" "Team-working skills" "Foreign language skills" "Customer handling skills"	"literacy skills" "numeracy skills" "Problem solving skills" "Planning and organisation skills"	
	"How would you best describe your skills in relation to what is required to do your job?" [Q22B / Q23B] *0: 0 My level of skill is a lot lower than required* *1-4: 1-4* *5: 5 My level of skill is matched to what is required* *6-9: 6-9* *10: 10 My level of skill is a lot higher than required*	"ICT skills" "Technical skills"	"Learning skills"	"Communication skills" "Team-working skills" "Foreign language skills" "Customer handling skills"	"literacy skills" "numeracy skills" "Problem solving skills" "Planning and organisation skills"	

Continuing Vocational Training Survey (CVTS)[10]	**"In your enterprise, which skills/competences are generally considered as most important for the development of the enterprise in the next few years? Tick the three most important skills/competences from the following list […]"** [A12]	"General IT skills" "IT professional skills"		"Team working skills" "Costumer handling skills" "Foreign language skills" "Oral or written communication skills"	"Management skills" "Problem solving skills" "Office administration skills" "Numeracy and/or literacy skills"	"Technical, practical or job-specific skills" "Other skills not listed above"
	"In 2020, which skills/competences targeted by CVT courses were the most important ones in terms of training hours? Tick the three most important skills/competences from the following list […]" [C5]	"General IT skills" "IT professional skills"		"Team working skills" "Costumer handling skills" "Foreign language skills" "Oral or written communication skills"	"Management skills" "Problem solving skills" "Office administration skills" "Numeracy and/or literacy skills"	"Technical, practical or job-specific skills" "Other skills not listed above"

[10] Source: CVTS 6 manual – Version 1.1 (12 September 2019) (https://circabc.europa.eu/sd/a/fae1ed15-c64b-430e-8e72-250ea1b2424c/1_CVTS6_manual_V1.1%202019-09-12.pdf)

Opinion survey on vocational education and training in Europe[11]	**"Would you say that you develop the following skills at upper secondary education?"** [Q14a] *1: Yes definitely* *2: Yes, somewhat* *3: No, not really* *4: No, not at all*	"Science and technology skills" "Digital and computer skills"	"The ability to be creative" "Sense of initiative and entrepreneurship" "Cultural awareness (appreciation of music, performing arts, literature and visual arts)"	"Communication skills (M)" "Speaking a foreign language (M)" "Social and civic competences to engage in active democratic participation" "The ability to work with others"	"Mathematical skills" "The ability to think critically" "The ability to pursue and organize your own"	
	"Would you say that you developed the following skills when you were at upper secondary education?" [Q14b] *1: Yes definitely* *2: Yes, somewhat* *3: No, not really* *4: No, not at all*	"Science and technology skills" "Digital and computer skills"	"The ability to be creative" "Sense of initiative and entrepreneurship" "Cultural awareness (appreciation of music, performing arts, literature and visual arts)"	"Communication skills (M)" "Speaking a foreign language (M)" "Social and civic competences to engage in active democratic participation" "The ability to work with others"	"Mathematical skills" "The ability to think critically" "The ability to pursue and organize your own"	

[11] Source: Cedefop European public opinion survey on vocational education and training; (https://www.cedefop.europa.eu/files/5562_en.pdf)

Future of jobs survey[12]	**Skill demands in 2018 and 2022** [13]	"Technology design and programming" "Technology installation and maintenance" "Technology use, monitoring and control"	"Active learning and learning strategies" "Attention to detail, trustworthiness" "Coordination and time management" " Manual dexterity, endurance and precision" "Quality control and safety awareness"	"Leadership and social influence" "Emotional intelligence" "Memory, verbal, auditory and spatial abilities" "Management of personnel" " Visual, auditory and speech abilities"	"Analytical thinking and innovation" "Creativity, originality and initiative" "Critical thinking and analysis" "Complex problem-solving" "Reasoning, problem-solving and ideation" "System analysis and evaluation" "Management of financial, material resources"	

[12] Source: The Future of Jobs Report 2018 (http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf)
[13] Exact wording of question is not public.

					"Reading, writing, math and active listening"	
Survey of Adult Skills[14]	**"In your [job | last job], how often [do | did] you usually …"** [G_Q01 / G_Q02 / G_Q03] *1: Never* *2: Less than once a month* *3: Less than once a week bat at least once a month* *4: At least once a week but not every day* *5: Every day*	"use email?" "use the internet to better understand issues related to your work?" "conduct transactions on the internet […]" "use spreadsheet software […]" "use a word processor […]" "use a programming language to program or write			"read directions or instructions?" "read letters, memos or e-mails?" "read articles in newspapers, magazines or newsletters?" "read articles in professional journals or scholarly publications?" "read books?"	

[14] Source: International Master Questionnaire (http://www.oecd.org/skills/piaac/BQ_MASTER.HTM)

		computer code” “participate in real-time discussions on the internet, for example online conferences, or chat groups?”			“read manuals or reference materials?” “read bills, invoices, bank statements or other financial statements?” “read diagrams, maps or schematics?” “write letters, memos or e-mails?” “write articles for newspapers, magazines or newsletters?” “write reports?” “fill in forms?” “calculate prices, costs or budgets?”	

					"use or calculate fractions, decimals or percentages?" "use a calculator – either hand-held or computer based?" "prepare charts, graphs or tables?" "use simple algebra or formulas?" "use more advanced math or statistics […]"	
	"Did you _______ in jour [job | last job]?" [G_Q04] *1: Yes* *2: No*	"use a computer"				

	What level of _____ [is | was] needed to perform your [job | last job]? [G_Q06] *1: STRAIGHTFORWARD […]* *2: MODERATE […]* *3: COMPLEX […]*	"computer use"				
	"Do you think you [have / had] the _______ you [need / needed] to do your [job / last job]? [G_Q07] *1: Yes* *2: No*	"computer use"				
	"Has a lack of ________ affected your chances of being hired for a job or getting a promotion or pay raise?" [G_Q08]	"computer skills"				

	1: Yes *2: No*					
	“In everyday life, how often do you usually …” [H_Q01 / H_Q02 / H_Q03] *1: Never* *2: Less than once a month* *3: Less than once a week bat at least once a month* *4: At least once a week but not every day* *5: Every day*	“use email?” “use the internet to better understand issues related to your work?” “conduct transactions on the internet […]” “use spreadsheet software […]” “use a word processor […]” “use a programming language to program or write computer code” “participate in real-time discussions on the			“read directions or instructions?” “read letters, memos or e-mails?” “read articles in newspapers, magazines or newsletters?” “read articles in professional journals or scholarly publications?” “read books?” “read manuals or reference materials?” “read bills, invoices, bank statements or	

		internet, for example online conferences, or chat groups?”			other financial statements?” “read diagrams, maps or schematics?” “write letters, memos or e-mails?” “write articles for newspapers, magazines or newsletters?” “write reports?” “fill in forms?” “calculate prices, costs or budgets?” “use or calculate fractions, decimals or percentages?” “use a calculator – either	

					hand-held or computer based?” “prepare charts, graphs or tables?” “use simple algebra or formulas?” “use more advanced math or statistics […]”	
	“[…] To what extent do the following statements apply to you?” [I_Q04] *1: Not at all* *2: Very little* *3: To some extent* *4: To a high extent* *5: To a very high extent*		“When I hear or read about new ideas, I try to relate them to real life situations to which they might apply” “I like learning new things” “When I come across something new, I try to relate it to what I already know”		“I like to get to the bottom of difficult things” “I like to figure out how different ideas fit together”	

			"If I don't understand something, I look for additional infor-mation to make it clearer"			
	"What is the lan-guage that you first learned at home in childhood AND STILL UNDERSTAND?" [J_Q05a1] *Selection of one language.*			[Language skills]		
	"What is the second language that you first learned at child-hood AND STILL UN-DERSTAND?" [J_Q05a2] *Selection of one language.*			[Language skills]		
	"What language do you speak most often at home?" [J_Q05b] *Selection of one language.*			[Language skills]		