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Job tasks in the EU: Implications for skills and labour shortages

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Contents

Introduction and literature review

Much of modern labour analysis relies on the analysis of job tasks, which describe labour processes – what people do at work and how they work. This approach underlies many influential ideas that have taken root in policy discourse, such as automation affecting routine jobs the most and the supposed 'polarisation' of employment. It has been used to make predictions about potential changes to labour markets, such as estimating the share of the workforce that is vulnerable to offshoring or the share of workers that could telework during the COVID-19 pandemic. Analysing tasks helps us understand the complex effects of computers on work organisation or gender differences in power and control within jobs.

The idea of analysing tasks to understand labour market trends is well-established in sociological and economic literature. Braverman (1974) provided a foundation for understanding how tasks are structured as part of labour processes. He argued that technological advancements and scientific management techniques, such as those pioneered by Frederick Taylor, lead to the fragmentation of tasks and the simplification of work processes, a process known as 'deskilling'. His analysis thus connected work in terms of task content – the process of material transformation that workers operate on – with forms of work organisation that may adversely affect job quality.

The contemporary economic literature for analysing job tasks follows Autor et al. (2003), who argued that the task content of work acts as a determinant of labour market outcomes. It classified tasks into routine and non-routine, further distinguishing them by cognitive or manual dimensions. Routine tasks are those that follow explicit rules and are often repetitive, which, they argued, makes them more susceptible to automation. Non-routine tasks, in contrast, require problem-solving, creativity or interpersonal skills, which were believed to be less vulnerable to being replaced by machines. Autor (2013) provided an overview and research agenda of the task approach to economic analysis, which has considerably expanded since.

The first application of the task approach concerns job polarisation, which refers to growing employment in high- and low-wage jobs at the expense of middle-wage jobs, a trend documented extensively in the literature in the United States, since Autor et al. (2006). In this view, the analysis of tasks plays a crucial role in explaining polarisation. Acemoglu and Autor (2011) and Autor and Dorn (2013) argued that technological advancements, particularly in information technology, have automated routine tasks that were once the core of middle-wage jobs, leading to their decline. High-wage jobs, typically involving non-routine cognitive tasks, and low-wage jobs, often involving non-routine manual tasks, have seen relative growth. Subsequent research has called into question whether labour markets outside the United States also experience polarisation. Evidence from the EU and other economies suggests that there are in fact different patterns of occupational change, including 'upgrading' of the occupational structure (Eurofound et al., 2015; Fernández-Macías, 2012; Torrejón Pérez et al., 2025).

The literature on automation also uses the task approach to predict which jobs are most exposed to digital technology in general, and artificial intelligence (AI) in particular. Frey and Osborne (2017) applied machine learning to estimate the probability of computerisation for over 700 occupations using task-based data, concluding that jobs involving routine tasks are the most vulnerable. This approach has been widely adopted in subsequent studies, leading to various predictions of labour market change due to technological advances. Arntz et al. (2016) criticised some of these studies for overestimating the potential for automation by not accounting for task variability within jobs and the ability of workers to adapt tasks to new technologies. With the increasing use of robots, mostly in the manufacturing sector, several studies have used the task approach to explain the impact of automation in general – and robotics in particular – on employment and local labour markets (Acemoglu and Restrepo, 2019, 2020). Researchers have mapped recent improvements in the capabilities of AI to estimate which occupations are most 'exposed' to AI – though exposure does not necessarily imply that those occupations will be displaced (Felten et al., 2021; Tolan et al., 2021).

In addition to providing a framework to understand the impact of technological change on work, the analysis of job tasks also explains developments in international trade. Blinder (2009) argued that jobs involving tasks that can be digitised or do not require physical presence are more likely to be offshored. This insight has driven a substantial body of research examining the vulnerability of different occupations to globalisation. Tasks that require face-to-face interaction, local knowledge or are culturally specific are less susceptible to offshoring. Grossman and Rossi-Hansberg (2008) further developed a theoretical model explaining how the offshoring of tasks, rather than entire jobs, affects wage structures and employment in developed countries.

During the COVID-19 pandemic, the task approach was also used to understand the feasibility of remote work. By analysing the specific tasks and activities that can be performed remotely, researchers can identify which jobs and industries are most susceptible to telework (Dingel and Neiman, 2020). Based on pre-COVID-19 occupation data on tasks, Sostero et al. (2020) estimated that around 37 % of EU jobs were 'technically teleworkable', to the extent that they did not require high levels of physical interaction with people, objects and machinery. This estimate was consistent with the prevalence of working from home measured during the 2020 COVID-19 lockdowns.

The task approach also helps explain how differences in work organisation result in gender differences in power and control in the workplace, even for similar occupations (Fana et al., 2023).

Overall, the task approach has proved to be useful to retrospectively explain the impact on labour markets of changing technology, trade and work organisation. The same data and underlying approach are also used to make predictions about future labour market developments, including offshoring, telework and the impact of technological developments, from computers to robots and AI.

The concept of task is closely related to that of skill, which is more often used in policy discussions. Skills are originally defined as the ability to perform tasks (Acemoglu and Autor, 2011; Rodrigues et al., 2021). Research on both issues shares some of the same data sources, but the perspective and policy prescriptions surrounding the two concepts are quite different.

EU skills policy focuses on education and training of workers and jobseekers. It is focused on closing 'skill mismatches' and 'skill gaps', assuming that employers have sophisticated skill requirements that the workforce may be unable to fulfil. For individuals, skills are presented as key to improving employability and increasing earning potential. At the sectoral and national levels, reskilling and upskilling are frequent prescriptions for driving the green and digital transitions and improving competitiveness, as recently mentioned in the European Commission's communication on the European skills agenda ([1]).

Despite the conceptual different between tasks and skills, data on tasks can provide useful evidence for ongoing policy debates on labour and skills shortages and skills policy (European Commission, 2025).

In the context of pressing policy concerns about labour and skills shortages, the task approach can provide a broad view, by showing the aggregate differences between occupations that are experiencing shortages and those that are not. The drivers of specific skills and labour shortages are complex and probably vary by Member State, sector and occupation. Nevertheless, we can attempt a general comparison: if we observe that shortage occupations involve more cognitive or digital tasks compared to other occupations, this could indicate that the workforce does not have enough workers with cognitive skills to fill those positions. If, on the other hand, we observe that shortage occupations tend to involve more strenuous physical tasks or have forms of work organisation that result in higher routine and less autonomy, this may suggest that the issue is not with the supply of skills, but with job quality and working conditions, as suggested by Eurofound et al. (2024) and Zwysen (2024).

Likewise, skills policies like the union of skills respond to concerns that the workforce lacks essential skills for the workplace, like literacy, numeracy or digital literacy. Task-based surveys of workers can establish the extent to which tasks involving literacy, numeracy or the use of digital devices are actually used in the workplace. They also allow us to capture the extent of skill underuse, looking at the frequency of cognitive and digital tasks of educated workers.

This paper has two main objectives.

Firstly, to present new evidence on job tasks across the EU from the 2022 EU LFS, along individual and structural characteristics: occupation, income level, gender, firm size and Member State. This data is among the few sources that allow the comparison of task profiles between Member States even for the same detailed occupation, which reveals surprising differences.

Secondly, to show how the task perspective can illustrate the structural change of EU labour markets over the last decade in terms of skill level and job quality. The same data can be used to make general comparisons between shortage occupations and other occupations, and to check the rates at which cognitive and digital skills are used in the workplace.

The paper is structured as follows: the next section presents an overview of the different data sources and measurements commonly used for task analysis and presents new data from the EU LFS module on job skills. Then, this data is used to illustrate the difference in task profiles between occupations, along the income distribution, by gender, by firm size and between Member States. This is followed by an overview of structural changes in the labour market from the perspective of tasks, including analysing the differences in task profiles of shortage occupations and the utilisation of cognitive skills. The concluding remarks discuss the advantages and limitations of the data and its analysis and propose future applications of it.

([1]) Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions – European Skills Agenda for sustainable competitiveness, social fairness and resilience, COM(2020) 274 final of 1 July 2020, https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52020DC0274.

1 Data on job tasks

This section provides a brief overview of the features, advantages and limitations of existing sources of data on tasks, before presenting new data from the EU LFS module on job skills, which is used throughout the paper.

How are tasks measured?

The numerous empirical studies in the task-based literature rely on a limited set of data sources, developed for different purposes, with different methodologies and somewhat different operationalisations of the concepts of 'tasks' and 'skills'. This subsection provides a short overview and comparison of sources, partly based on Bisello et al. (2021), who provided a synoptic treatment of the data.

O*Net

The most widely used data source in the related literature is O*Net (Occupational Information Network), an online database developed by the US Department of Labor and its agency the Employment and Training Administration, which has been describing the labour market of the United States since 1998 through continuous updates. O*Net is organised along a complex content model (2), oriented both to the characteristics of workers and jobs, and between different occupations. Importantly for scientific research, it lists detailed occupation titles, related to the US Standard Occupational Classification, and for each of them presents data on the types of tasks performed. These range from 41 generalised work activities measured for all jobs (such as 'How important is performing for or working directly with the public to the performance of your current job?') to nearly 20 000 distinct task statements that are specific to detailed occupations (such as 'Apply protective coating of fluoride to teeth' for detailed occupation 31-9091.00 – Dental Assistants). The sources for such statements include surveys of experts and samples of workers in each occupation. The combination of generic and specific task statements in O*Net allows researchers to classify occupations in terms of broad task characteristics – such as the frequency and complexity of routine, cognitive and manual tasks – but also to analyse one by one the types of detailed occupation-specific tasks they believe are more susceptible to automation.

Despite being designed to describe the labour market of the United States, O*Net data is sometimes used to analyse labour market developments in Europe and elsewhere when comparable data of similar scope and quality is lacking. This is achieved using crosswalks between occupational classifications, relying on the assumption that the task content of occupations does not vary much between Member States – an assumption that is questionable. A similar data source is the Italian Indagine Campionaria sulle Professioni [Occupations Sample Survey] (ICP), administered by l'Istituto nazionale per l'analisi delle politiche pubbliche [National Institute for Public Policy Analysis], which implemented a questionnaire based on O*Net in 2007, 2012 and 2023. ICP is arguably the richest source of task-based data in the EU, and was used, among other things, as a primary source to estimate the share of EU jobs that are 'teleworkable' – meaning that they could performed remotely (Sostero et al., 2020).

Survey of Adult Skills (PIAAC)

The Survey of Adult Skills is a large-scale international survey designed to assess key cognitive and workplace skills required for individuals to participate effectively in society and the economy. It assesses the proficiency of adults aged 16 to 65 in literacy, numeracy and problem-solving in technology-rich environments. Importantly for task-based research, it measures the extent to which these skills are used at work. The survey is part of the Programme for the International Assessment of Adult Competencies (PIAAC), developed by the Organisation for Economic Co-operation and Development (OECD), and is run in different countries over 10-yearly cycles.

European Working Conditions Survey

The European Working Conditions Survey (EWCS), conducted by Eurofound (the European Foundation for the Improvement of Living and Working Conditions), provides comprehensive data on working conditions across Europe. First launched in 1990, the EWCS collects detailed information from workers in over 30 European countries, covering a wide range of topics including employment status, job quality, work organisation, work–life balance, physical and psychosocial risks and access to training and representation. The EWCS samples workers, offering insights into how broader economic, institutional and social changes affect working life. It emphasises both objective and

(2) O*Net Resource Center, 'The O*Net Content Model', O*Net website, 1 July 2025, https://www.onetcenter.org/content.html.

subjective dimensions of work, allowing researchers to examine not only structural aspects – such as hours worked or contract types – but also subjective assessments of well-being, autonomy and job satisfaction. The survey's harmonised methodology allows comparisons between countries and to some extent over time, though its scope has expanded significantly over the years.

The EWCS measures several variables of interest for task-focused research. These include several questions related to work organisation – autonomy, teamwork, repetitiveness, standardisation, uncertainty – and some on task content, such as use of strength and proxies for creativity ('solving unforeseen problems' and 'apply[ing] own ideas in your work').

European skills, competences, qualifications and occupations

ESCO (European skills, competences, qualifications and occupations) is the European multilingual classification of skills, competences, qualifications and occupations, developed by the European Commission and started in 2011. It is structured as a dictionary, along different pillars providing hierarchical classifications of nearly 14 000 skills and competences, over 3 000 occupations, and the relation between them and their translation into all EU languages. The data comes primarily from groups of sectoral experts managed by the European Commission, though the methodology is increasingly data-driven. ESCO provides rich details on the skills required by all kinds of jobs, which is increasingly used for research on skills and tasks. However, the level of detail in skill requirements varies substantially by industry and occupation group. Unlike O*Net, ESCO lacks a survey of jobholders that would provide empirical measurements of skill requirements, skill use or other job characteristics.

Online job advertisements

Data from online job advertisements (OJA, or 'job postings') are an increasingly popular source of information about the changing skills and tasks of jobs. In principle, OJA can help continually monitor the amount of job openings for different job titles, the skills required and sometimes the terms of employment like salary and benefits. OJA is considered particularly useful for monitoring the rise of new skills, particularly those related to emerging technologies. However, it cannot measure the extent to which different skills are used in the workplace and there are several concerns about the data's representativeness and completeness: it tends to overrepresent high-skill occupations, particularly those in information and communication technology (ICT), relative to manual ones. It also better covers skills which are formal and standardised, typically associated with professional occupations, and it suffers from social desirability bias, with positive and soft attributes being overemphasised (see Sostero and Fernández-Macías, 2021).

The Eurofound–Joint Research Centre task framework and EU Tasks Database

Eurofound's research on tasks was started as part of the 2016 European Jobs Monitor (Eurofound et al., 2016), which described tasks as work processes, shaped by forms of organisation, which also affect job quality. Building on insights from Braverman's labour process theory, tasks describe the content of work (manual, cognitive and social tasks), but also the methods of work (routine, autonomy teamwork) and the tools of work (machines or digital). This was followed by an expanded a theoretical task framework (Fernández-Macías and Bisello, 2022) and corresponding data at the occupational and the sectoral level (Bisello et al., 2021). This EU tasks database initially relied on a combination of sources: Eurofound's European Working Condition Survey, the PIAAC from the OECD, and the ICP. In 2022, Eurostat developed an ad hoc module to the 2022 EU LFS based on the Eurofound–Joint Research Centre (JRC) task framework, which it called 'job skills'.

The EU LFS module on job skills

The 2022 EU LFS module on job skills is a new source of individual-level data on job tasks for the EU-27. The module on job skills was published in 2022 with respondents of the EU LFS aged between 15 and 74 who were then in employment or had left their last employment in the last 24 months. The resulting microdata contains responses from over 440 000 people from across the EU-27. The scale of the EU LFS sample allows us to compare the variation in task profiles for the same occupation between Member States, sectors or other dimensions.

The module surveyed respondents on 11 questions related to what people do at work, in addition to the standard set of socioeconomic characteristics collected by the EU LFS. These questions relate to a small number of task types, rather than a comprehensive dictionary like O*Net. Although some questions overlap with the EWCS and the PIAAC, the EU LFS modules simultaneously measured task content, methods and tools on a large scale at the EU-27 level for the first time.

The approach of the Eurofound–JRC task framework, and of the 2022 EU LFS ad hoc module on job skills, is to survey workers on what their job actually entails, independent of what it may require in principle. This provides a useful – and occasionally surprising – overview of the world of work in the EU.

However, it should be noted that the EU LFS module on skills was not designed to answer specific policy questions. It was carried out just once, which prevents comparisons over time.

Seven variables in the questionnaire relate to task content: strength, dexterity, reading, calculating, providing training, internal communication and external communication. The other four questions relate to the methods and tools with which tasks are performed. The first, digital, relates to the time spent working on digital devices. Another question relates to the degree of job autonomy of the respondent in terms of determining the order and content of tasks at work. The final two questions, also related to methods of work, measure the degree of job repetitiveness and standardisation (namely 'tasks precisely described by strict procedures').

Table 15 in Annex 1 gives an overview the structure and concepts from the task framework, the full wording of questions and responses in the EU LFS ad hoc module on job skills, with the identifiers as provided in the EU LFS and the variables derived from these questions, as used in this paper. Below, we describe the scale of responses to each question and their distribution in the microdata.

Questions on task content and digital devices

The questions on task content – strength, dexterity, reading, calculating, providing training, internal communication and external communication – along with the questions on digital devices, ask how often the respondent performs any of the tasks during the working time of their main or previous job.

The questions on task content collectively describe the type of job each respondent does, in terms of a few task attributes. Strength and dexterity both measure the extent of manual tasks – 'Time spent on doing hard physical work', 'Time spent on tasks involving finger dexterity' – and indicate physical requirements or manual skill. Reading and calculating 'Time spent on reading work-related manuals and technical documents', 'Time spent on doing relatively complex calculations' are cognitive tasks. As such, they are skills like literacy and numeracy, but the questions are not an assessment of the skill level of respondents, but rather a measure of how often these skills are actually used in the job.

Providing training, internal communication and external communication are examples of communication tasks. Among these, only training was described in the task framework, as 'teaching/training', as part of 'social tasks', alongside 'selling/influencing', 'serving/attending' and 'managing/coordinating'.

The responses to these questions can be interpreted in a few different ways. Providing training can be a sign of knowledge transmission within organisations, which can improve productivity and innovation. Interestingly, the question is formulated in terms of imparting training, whereas most surveys on the subject tend to ask about receiving training, whether formal or not. Internal and external communication can be seen as tasks requiring so-called soft skills, but the purpose and medium of communication is left unspecified. Nevertheless, the extent of communication can also be used as a predictor of whether a particular occupation is amenable to telework, as argued in Sostero et al. (2020). The question on the use of digital devices is the only one in the group that does not strictly address the nature of work being done (task content), but rather the tools with which it is performed. It provides an important measure of to what extent modern technology is adopted between Member States, sectors and firms of different sizes.

The responses to questions in this group (task content and digital devices) are expressed in a five-category frequency scale ranging from 'All or most of the working time' to 'None of the working time'. It should be noted that the responses are not mutually exclusive, and in principle respondents may reply 'All or most of the working time' to all of them. This allows us to capture combinations of tasks, such as whether a respondent reports both frequent physical tasks, reading for work and frequent use of digital devices.

Table 1 shows the distribution of responses for each question in the microdata. They show that a plurality of respondents indicate that their job does not require strength (when asked about 'Time spent on doing hard physical work', 40 % picked 'None of the working time'). The comparable figure, when asked about dexterity ('Time spent on tasks involving finger dexterity') is 55.7 %. However, a significant minority say their jobs require strength at least half of the working time (10.6 % 'Half or slightly more', 15.9 % 'All or most').

The non-response rate for each question ranges between 6.7 % for using digital devices to 9 % for providing training.

These figures provide a snapshot of the world of work in the EU today, with a plurality of workers not performing manual tasks (strength and dexterity), doing cognitive tasks (reading, calculating) little to some of the working time and a somewhat polarised use of digital devices (either relatively often or relatively little).

Table 1: Distribution of responses on task content and use of digital devices

Question \ Scale	All or most of the working time	Half of the working time or slightly more	Some of the working time	Little of the working time	None of the working time	n/a
Strength	15.9 %	10.6 %	11.8 %	14.4 %	40.0 %	7.3 %
Dexterity	9.5 %	6.7 %	8.3 %	12.0 %	55.7 %	7.9 %
Reading	5.3 %	8.5 %	18.0 %	27.3 %	33.0 %	7.9 %
Calculating	3.7 %	5.3 %	11.2 %	20.4 %	51.2 %	8.2 %
Providing training	7.5 %	7.0 %	14.1 %	20.3 %	42.2 %	9.0 %
External communication	15.0 %	12.6 %	17.7 %	21.7 %	24.2 %	8.8 %
Internal communication	15.0 %	16.3 %	24.9 %	23.5 %	12.0 %	8.3 %
Using digital devices	25.3 %	12.5 %	11.8 %	15.0 %	28.7 %	6.7 %

Source: *2022 EU LFS ad hoc module on job skills.*

Questions on standardisation and repetitiveness

The questions on repetitiveness (‘Repetitiveness of tasks in main or last job’) and standardisation (‘Tasks precisely described by strict procedures in main or last job’), taken together, are intended to measure the degree of routine associated with each job. In the literature, high degrees of repetitiveness and standardisation are considered to be requirements for the automation of job tasks, though the empirical evidence for this proposition remains mixed.

Responses to both questions are expressed on a five-value scale, ranging from ‘To a very large extent’ to ‘To no extent’. Nearly half of respondents say that their job is repetitive to a large or very large extent (27.9 % and 19.8 % respectively, or 47.7 % of all respondents), with only a minority of 7.5 % respondents saying that their job is not repetitive at all. In terms of standardisation, responses are more varied: 37.1 % of respondents say that their job is described in terms of strict procedures to a large or very large extent, but 32.2 % say theirs is standardised little to no extent.

Question on job autonomy

The question on job autonomy asks about the degree of autonomy for both order and content of tasks. It can be interpreted as a contributor to job quality, in the sense that it measures the empowerment of individual respondents to choose what they do at work and how they do it.

The response scale combines order and content over three levels: ‘Large’, ‘Some’, or ‘Little to no’ autonomy, resulting in nine possible responses. The responses tend to be correlated between the autonomy for order and content: 23.3 % say that they have ‘Large or very large’ autonomy on both order and content, 17.5 % say they have ‘Some’ autonomy on both, and 23 % say they have ‘Little to no’ autonomy on both. The next most common responses are large autonomy on order and some on content (8.1 %) or some autonomy on order and little on content.

Table 2: Distribution of responses on repetitiveness and standardisation

Question \ Scale	To a very large extent	To a large extent	To some extent	To little extent	To no extent	n/a
Repetitiveness	19.8 %	27.9 %	25.1 %	10.3 %	7.5 %	9.5 %
Standardisation	16.4 %	20.7 %	19.8 %	14.1 %	18.1 %	10.1 %

Source: *2022 EU LFS ad hoc module on job skills.*

Table 3: Distribution of responses on job autonomy

Job autonomy (order and content of tasks)	Share
Large or very large autonomy on both order and content	23.3 %
Large or very large autonomy on order and some autonomy on content	8.1 %
Large or very large autonomy on order and little or no autonomy on content	3.4 %
Some autonomy on order and large or very large autonomy on content	3.2 %
Some autonomy on both order and content	17.5 %
Some autonomy on order and little or no autonomy on content	7.6 %
Little or no autonomy on order and large or very large autonomy on content	1.2 %
Little or no autonomy on order and some autonomy on content	2.7 %
Little or no autonomy on both order and content	23.0 %
n/a	10.1 %

Source: *2022 EU LFS ad hoc module on job skills.*

Taken together, the 11 questions can describe work in various ways, including what it involves and how it is performed. The next subsection develops a smaller number of aggregate task indices from these questions, to better visualise and analyse differences between groups of occupations, sectors and Member States.

Constructing task indices

In this section, we aggregate the 11 questions of the module into six composite task indices at the respondent level. First, we transform the ordered categorical responses of the survey into numeric values. Then, we aggregate the values into task indices, based on the theory of the task framework on which the module is based.

Transforming categorical values into numerical values

The different categorical scales are encoded using following schema, which is conventionally used at Eurofound to analyse EU LFS microdata expressed in the same scales (Table 4).

Table 4: Encoding of frequency and extent scale

Questions	Scale	Encoding
Strength, dexterity, reading, calculating, internal communication, external communication, providing training, digital	All or most of the working time	1
	Half of the working time or slightly more	0.5
	Some of the working time	0.25
	Little of the working time	0.1
	None of the working time	0
Routine, standardisation	To a very large extent	1
	To a large extent	0.5
	To some extent	0.25
	To little extent	0.1
	To no extent	0

The question on job autonomy combines responses about autonomy on the order and content of tasks. We therefore split these two components and then derive a single variable for job autonomy as the minimum of the degree of autonomy for either order or content (Table 5).

Table 5: Encoding of autonomy scale

Scale for job autonomy	Encoded variables		
	Autonomy on order	Autonomy on content	Job autonomy (minimum of two)
Large on both order and content	1	1	1
Large on order and some on content	1	0.5	0.5
Large on order and little (or no) on content	1	0	0
Some on order and large on content	0.5	1	0.5
Some autonomy on both order and content	0.5	0.5	0.5
Some on order and little (or no) on content	0.5	0	0
Little (or no) on order and large on content	0	1	0
Little (or no) on order and some on content	0	0.5	0
Little (or no) on both order and content	0	0	0

Aggregating and interpreting the task indices

We aggregate the encoded variables into six task indices as shown in Table 6, which considers both the structure of the task framework and the empirical correlation between the variables (see Annex 2 for details). The aggregation is performed at the individual respondent level, by averaging the numeric variables in each group.

Table 6: Aggregating task indices

Variable	Task index
Strength	Manual
Dexterity	
Reading	Cognitive
Calculating	
Providing training	Communication
Internal communication	
External communication	
Digital devices	Digital tools
Job autonomy (minimum of order and content)	Autonomy
Repetitiveness	Routine
Standardisation	

The six task indices – manual, cognitive, communication, digital tools, autonomy and routine – are first computed for each individual respondent and values can range over the scale [0–1], where higher values correspond either to more time spent on the task, a larger extent of routine or standardisation or a higher level of autonomy. The numeric coding thus allows us to meaningfully compare the average values – whether the underlying survey question measures frequency, intensity or autonomy.

The task indices can be averaged across groups of respondents, such as those in the same occupation, sector or of the same sex. For example, the cognitive index includes reading and calculating, which are both on the frequency scale. If the average cognitive task index for a given occupation were equal to one, it would mean that all respondents in that occupation indicated that they read and calculate 'All or most of the working time', though that is unlikely to happen in practice.

The next sections discuss how task indices vary along several dimensions, including occupation, sector, Member State, firm size, sex and income distribution. This establishes which task indices vary the most along different key socioeconomic variables and prepares for a systematic comparison between groups of policy interest, including key economic sectors and shortage occupations.

2 The variation in task profiles

This section compares the task indices across different subgroups, including between occupations, sectors of economic activity, firm sizes or Member States. The task profiles of occupation groups and sectors vary mostly as expected. For instance, managers have less manual and more cognitive tasks than, say, plumbers. However, the differences in the task indices between Member States cannot merely be explained by different industrial and occupational structures, but instead reflect task differences within the same jobs. For example, among office clerks in Luxembourg, 40 % say that they have a high level of control over the content of their tasks, whereas less than 4 % of Greek clerks say the same. In other words, there is a strong Member State-level component to the level of task profiles even when accounting for differences in occupational structure.

Task differences between occupations

Task profiles vary most clearly by occupation. This is natural, as occupations are designed to be groups of jobs with similar tasks. The task indices, particularly manual, cognitive and communication, closely follow the ordering of occupations in the International Standard Classification of Occupations (ISCO) defined by the International Labour Organisation (ILO). ISCO is ordered based on 'skill levels' defined by the ILO as 'a function of the complexity and range of tasks and duties to be performed in an occupation' and measured based either on the nature of work tasks, the level of formal education required or the amount of on-the-job training or experience required.

The occupational ordering thus correlates with several of the task indices measured in the ad hoc module, as seen in Figure 1. Most obviously, jobs in managerial, professional and clerical occupations (ISCO 1–4) feature low levels of manual tasks, higher levels of cognitive tasks, communication and use of digital devices. As striking examples, in terms of the underlying survey questions, less than 5 % of respondents in professional or clerical occupations (ISCO 2 and 3) report that their work requires hard physical work (strength) 'All or most of the working time', and they also are the occupation with the highest share of people reporting reading 'All or most of the working time', at 9.5 % of respondents.

By contrast, agricultural workers, craftspeople, machine operators and elementary occupations (ISCO 6–9) tend to have higher levels of manual tasks and lower level of cognitive and communication. Over 30 % of respondents in agricultural occupations, elementary occupations and craft and related trades say that their job requires strength 'All or most of the working time'.

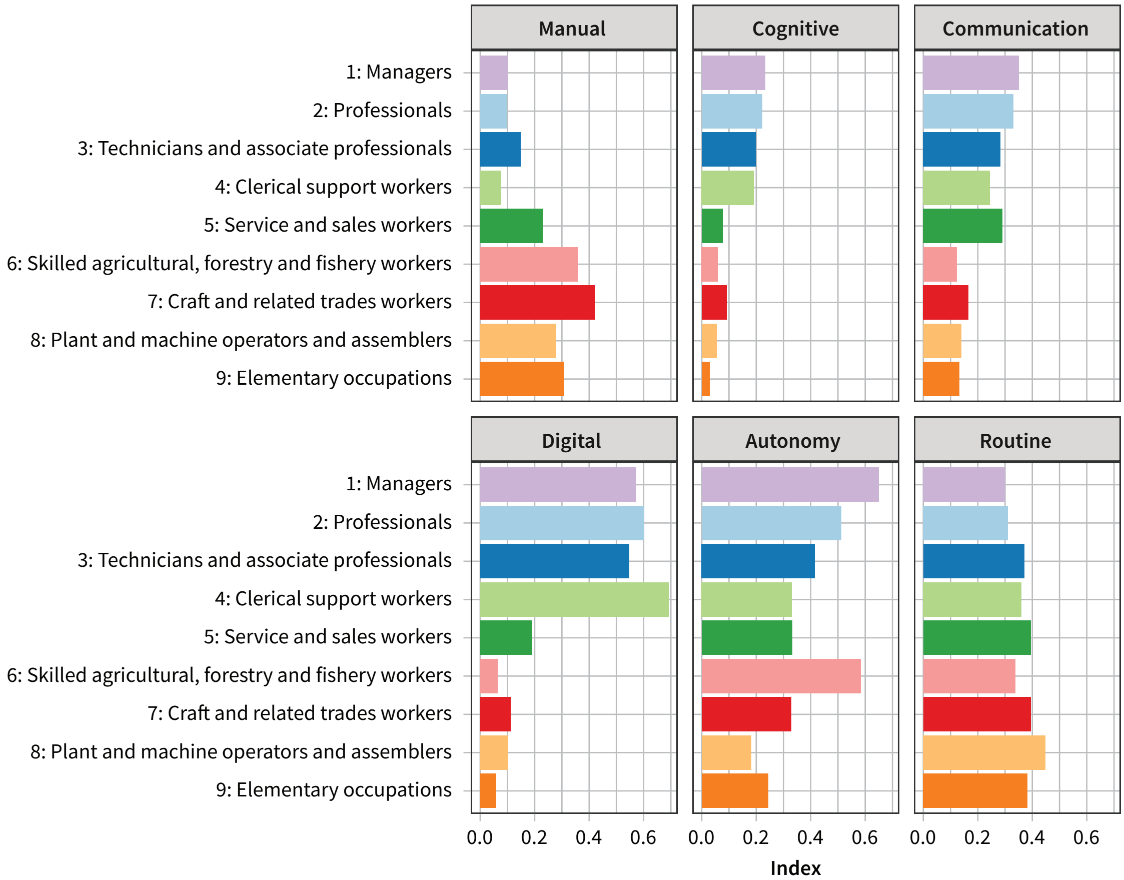
Service and sales workers (ISCO 5) fall somewhere in between these two groups, with intermediate levels of manual tasks, low levels of cognitive tasks but relatively high levels of communication. These intermediate values likely stem from the heterogenous nature of this type of service occupations, which includes occupations in retail trade (ISCO 522: Shop salespersons), in healthcare (532: Personal care workers in health services), in restaurants (513: Waiters and bartenders) and in education (531: Child care workers and teachers' aides).

The task indices related to digital devices and autonomy also vary considerably and mostly according to the ISCO hierarchy: white-collar managerial, professional and clerical occupations (ISCO 1-4) make frequent use of digital devices, while other occupations do not: the share of respondents reporting using digital devices all or most of the working time is over 40 % for clerks, professional, technicians and associate professionals, but less than 10 % for service workers, plant and machine operators and assemblers, craftspeople, elementary occupations and agricultural workers. We should note that, unlike other task indices, the digital index is the only one that is made up of a single survey question, so we may expect to see more variance in the aggregate than other indices like manual or cognitive, which average variables that are not perfectly correlated (see Figure 16 in Annex 2).

In terms of autonomy, there is a visible gradient even within white-collar occupations, with managers having more autonomy than professionals, who in turn have more than technicians and clerks. Among other occupation groups, skilled agricultural workers report the second-highest level of autonomy after managers. In terms of autonomy in the content of tasks, 53 % of managers and 48 % of agricultural workers report having high autonomy, but only 12.7 % of plant and machine operators report the same.

In terms of routine, the occupational pattern is less pronounced. Although occupations that are higher in the ISCO hierarchy tend to have lower values, the differences are not as pronounced as with other indices.

Figure 1:Task indices for occupation major groups (ISCO one-digit)



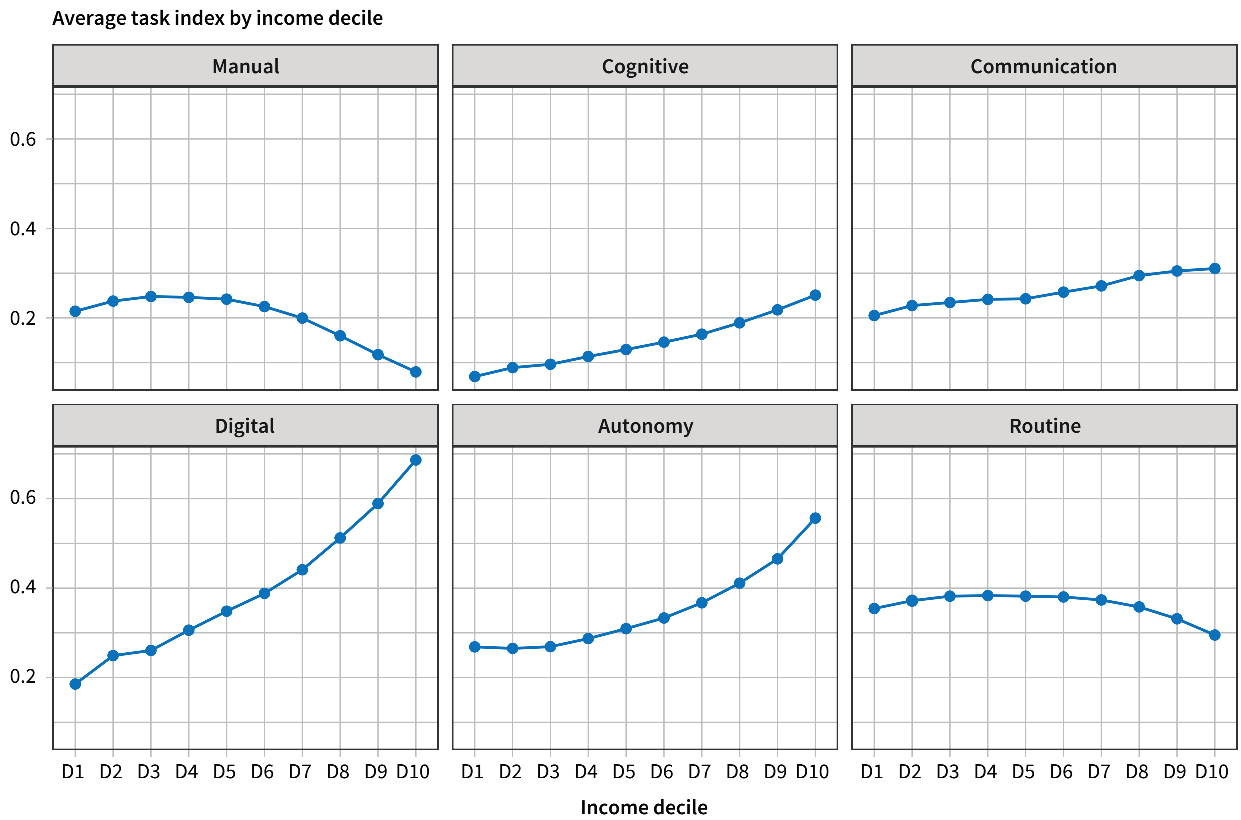
Note: *Each panel represents the how the corresponding average task index varies for occupation major groups (ISCO one-digit). Each task index can range between 0 (lowest possible value) to 1 (highest possible value).*
Source: *2022 EU LFS ad hoc module on job skills.*

Overall, the variation in task profiles between major occupation groups appears mostly as expected. Nevertheless, a few features stand out. The first is the relatively low absolute values of the indices for cognitive skills, below 0.3 even for white-collar occupations, which indicates that, no workers in these occupations spend most of their time either reading or calculating. Since the survey question specifically asks about 'relatively complex calculation' we may expect this to be confined to a small subset of specialist occupations, but that does not account for the low levels of reading, which is examined later in the paper. By comparison, the values of the digital index are high, in the range of 0.5–0.6 for ISCO 1–4 occupation groups, indicating that on average they spend more than half of their working time using digital devices. In terms of autonomy, it is perhaps surprising to see workers in agriculture, forestry and fishery report among the second-highest average levels of autonomy. This may relate to the share of people surveyed in the sector working on their own account. Later in this section, we analyse how task profiles (particularly autonomy) vary by firm size, including self-employment. Finally, considering the importance of the concept of 'routine' in task-based literature, especially since Autor et al. (2003), it is notable how little variation there is between occupations in the reported level of routine. The fact that otherwise different occupation groups report similar levels of routine may partly stem from the underlying questions being relatively subjective – reporting the level of repetitiveness and standardisation in one's job – but may also reflect that work organisation can vary more between firms than between jobs, which this worker-level survey is not equipped to measure.

Task differences along the income distribution

Occupation groups clearly differ in terms of the type of tasks they perform, but they also have significantly different income levels. Therefore, task profiles may also vary along the income distribution. Recent releases of the EU LFS microdata include information on the level of income of the respondent relative to the national income distribution. Income levels are presented in 10 deciles, which divide each Member State's population into 10 equally sized groups and rank them by income levels, from D1 (respondents with the

Figure 2: Variation in tasks along the income distribution



Note: *Each panel represents the how the corresponding average task index varies along the income distribution. The horizontal axis ranks respondents from the lowest income group (D1) to those in the highest income group (D10). The vertical axis shows the average value of the task index, which can range 0 (lowest possible value) to 1 (highest possible value).*
Source: *2022 EU LFS ad hoc module on job skills.*

lowest income level) to D10 (those with the highest income).

Figure 2 shows how the different task indices vary on average along the income distribution. Several notable patterns emerge. Both manual and cognitive task indices (top-left and bottom-right panel) show a hump-shaped distribution, with a peak around D3 for manual tasks and D4 for routine tasks. This means that the most routine and manually intensive jobs are somewhere in the mid to low portion of the income distribution but are not among the very lowest paid. The manual task intensity – and, to a lesser extent, the routine intensity – is lower for higher-income groups (D5-D10), but also for lower-income groups (D1-D2). All other indices – cognitive tasks, communication, digital and autonomy – continuously increase along the income distribution, albeit to different extents. This means that, on average, the higher paid a respondents is, the more their job features cognitive tasks, communication, use of digital devices and high levels of autonomy.

There are several explanations for these different patterns. The similar hump-shaped patterns for manual and routine tasks likely capture the same types of occupations: namely, low-to-mid-level manufacturing jobs tend to have among highest levels of manual and routine components, and happen to sit somewhere in the middle of the income distribution. By comparison, lower-paid jobs, typically in the service sector tend to be less routine, and less manual, insofar as they don't necessarily require high levels of strength and dexterity. Higher-paid occupations, such as technical and professional occupations are less manual and somewhat less routine. This pattern is consistent with findings for the United States (Autor et al., 2003) and for the EU (Eurofound et al., 2016).

The fact that all other task indices increase monotonically results from how tasks are bundled into jobs, both for reasons of skill and status, and how the task content relates to forms of work organisation and job quality. One possible reading is that the task content of jobs results in a wage premium for cognitive skills: those jobs that feature higher levels of cognitive tasks, use of digital tools and communication require more of the corresponding skills, which can be scarce, and command a higher income. At the same time, higher-income jobs enjoy more autonomy (increasingly so at the very top of the income distribution) and lower levels of routine, which decreases from the median income group (D5) to the highest income group (D10).

Higher levels of autonomy and lower levels of routine are desirable aspects of job quality and correlate with high income. Again, this can be partially explained because of relative scarcity of cognitive skills – workers with higher levels of cognitive, digital and communication skills have better bargaining power both for wages and working conditions – and also shows that job tasks are bundled based on questions of status, in addition to the technical needs of the production process.

Task differences by gender

Another important difference in the task profiles relates to the gender of the respondents. Women and men tend to work in different types of occupations, and this results in gendered differences in the average task content of work.

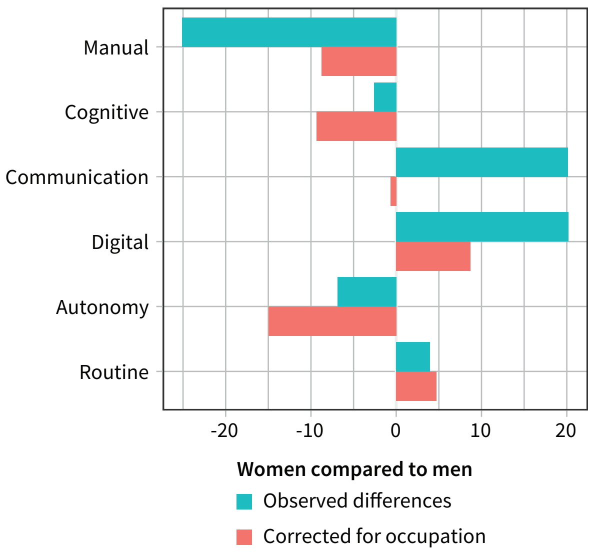
When comparing the task differences between women and men, we may want to look both at the aggregate gender differences by gender throughout the workforce – which reflect the average task profile of women and men in employment – as well as controlling for gendered occupational distribution, which accounts for the fact that women and men are not equally represented among all occupations. In many occupations, there is a substantial imbalance in the ratio of women and men employees: women make up over 90 % of people employed as Child care workers and teachers' aides (ISCO 531) and Personal care workers (ISCO 530), but less than 1.5 % of people employed in different building trades (ISCO 712, 711, 710). Accounting for gender differences in occupational distribution allows us to compare the tasks profiles of women and men in the same job, particularly the variables of autonomy and routine, which reflect forms of work organisation, where gender differences were shown for French workers in Fana et al., (2023). Fana et al. (2023) used French task-based data to show that there are significant differences in the average task profile of men and women even accounting for the type of task – particularly as they denote different forms of work organisation in the form of women experiencing on average lower autonomy and more control than men at work.

Based on data from the EU LFS from the ad hoc module on job skills, there are indeed some notable differences in the average task profiles for women and men, as summarised in Figure 3. On average, women tend to do manual tasks around 25% less often than men. In terms of the underlying survey responses, 18.8 % of men report doing hard physical tasks all or most of the working time, while only 12.6 % of women do. Correcting for gender differences in occupation, the difference is slightly smaller, at – 20 %. In aggregate, women seem to perform cognitive tasks slightly less often than men in their work (– 2.6 %): the share of those reading all or most of the working time is 5.7 % for women and 5.0 % for men, while the share of those calculating all or most of the working time is 3.8 % for men and 3.6 % for women. However, when controlling for occupational distribution, the figure is reversed, at 2.5 %.

More women tend to communicate frequently in their job (20.2 % more often than men), especially with people outside the organisation: nearly twice as many women report communicating 'All or most of the working time' than men (19.1 % compared to 11.3 %); the figure remains nearly unchanged after correcting for occupational differences (+ 19.9 %). They also make more use of digital devices (also + 20.2 %), with 28.8 % of women using them with the highest frequency, compared to 22.3 % of men.

In terms of work organisation, women experience slightly less autonomy than men: 25.8 % of women report high levels of autonomy in the content of tasks, versus 29.3 % of men. Finally, women experience slightly more routine: over 21 % of female respondents say that their job is repetitive to a high extent, compared to 18.4 % of men, but the share of male and female respondents reporting that their job is governed by strict procedure is nearly the same, at 16.3 % and 16.5 % respectively.

Figure 3: Task indices of women relative to men, % difference



Source: *2022 EU LFS ad hoc module on job skills.*

Most of the large differences in the task profiles between men and women result from them working in different occupations on average. Even when they do the same jobs as men, women tend to do manual tasks 6.8 % less often than men. Somewhat surprisingly, they tend do cognitive tasks 9.1 % less often than men and perform communication tasks at a similar rate. They are also 10 % more likely than men to use digital devices in their work. However, the biggest differences relate to methods of work: women report around 13 % less autonomy and 5 % more routine than men. These differences indicate that work organisation, which determines autonomy and routine, tends to adversely affect women on average.

Task differences by firm size

Task profiles vary not only along the characteristics of the individual respondent but also vary depending on the broader economic context. Notably, for employees, the size of the firm where the respondent works matters in terms of determining task profiles.

Task profiles can differ in firms of different sizes because of the industrial structure and work organisation. Large enterprises tend to be in different sectors than small and medium-sized enterprises. Based on the 2022 EU LFS, excluding the self-employed, in firms with less than 10 employees around 21 % of total employees were in wholesale and retail trade (the largest sector), followed by 8.5 % in accommodation and food service activities, and 7.3 % in manufacturing. Among firms with 250 employees or more, 23 % of employees worked in manufacturing, 17.5 % in health and social work, 14 % in public administration and less than 7 % in retail trade. In general, across the EU, small and medium-sized enterprises account for 99 % of all firms and 48 % of employment (3). These differences in industrial composition mean that on the whole larger organisations employ a somewhat different mix of occupations than smaller ones, including a larger share of factory workers, doctors and civil servants. In addition to composition, we also expect that forms of work organisation are different between small and large organisations, even within the same sector. Larger firm size allows for increased specialisation and a more fine-grained division of labour. On the one hand, this increases the variety of occupations required – most obviously, large firms have more need of dedicated personnel for human resources, accounting, finance and legal tasks – but division of labour can also reduce the amount of skill required for production tasks, which Braverman called 'de-skilling'. On balance, we would expect work in larger firms to be less manual and more cognitive on average. Because of their greater operational complexity, large organisations tend to put in place more explicit procedures to standardise processes and outputs. This may reduce worker autonomy and also make work more repetitive, increasing the extent of routine in the job.

Looking at the variation in task indices across firms of different sizes, without accounting for industry composition, appears to confirm some of these hypotheses and rejects others. The EU LFS survey regularly asks respondents to report the size of the firm they work with, currently expressed in five classes: 1–9 employees, 10–19, 20–49, 50–249 and 250 or more employees. If respondents are unsure, they may also choose to reply, 'Do not know but less than 10 people' (DK, < 10) or 'Do not know but 10 people or more' (DK, ≥ 10). This allows the creation of an approximate ranking of firm size, ranging from microenterprises, which employ fewer than 10 people (including DK, < 10), small enterprises, which employ between 10 and 49 employees (4) (including DK, ≥ 10, 10–19 and 20–49), medium-sized enterprises, which employ between 50 and 249 employees, up to large enterprises of 250 people or more. It is occasionally relevant to distinguish between the size class of 1–9 employees and 'Do not know but less than 10 people', although they seem to overlap conceptually, because the former also includes one-person firms, such as sole proprietorships (5).

As seen in Figure 4, many task indices vary somewhat between smaller and larger firms. The extent of manual work is higher in microenterprises than in large ones (excluding those of an unknown size). For example, respondents in the smallest firms are 58 % more likely to say that they do hard physical tasks 'All or most of the working time' compared to those in the largest firms (17.4 % of respondents in firms of 1–9 employees versus 11 % in firms of 250 employees or more. Cognitive tasks are more common in large firms than in small ones. Respondents in the largest firms are more than twice as likely to read very frequently than those in small ones (8.1 % in 250 +, v 3.9 % in 1–9, though absolute rates are low in both cases). Communication tasks on aggregate do not vary consistently across firm size, because the underlying indicators vary in different ways: employees in smaller organisations spend relatively more time communicating with people outside of the organisation and less time providing training or guidance, compared to their counterparts in larger firms, who spend more time on training and guidance and less on external communication. The extent of internal communication, perhaps surprisingly, is fairly consistent across firm sizes. On balance, the frequency of all communication activities is about the same for firms of different sizes.

The use of digital devices, by comparison, varies dramatically between smaller and larger firms – employees in larger firms use them much more often

(3) Eurostat, 'Micro & small businesses make up 99% of enterprises in the EU', Eurostat website, 25 October 2024, https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20241025-1.

(4) Here we assume that 'Do not know but more than 10 people' is more likely to indicate a small firm than a medium- or large-sized one.

(5) The original EU LFS questionnaire asks for an exact number between one and nine people, but for confidentiality reasons this is reported as '1–9' in the scientific use microdata used in this research. We assume that respondents of single-person firms would be more likely respond '1' rather than 'Do not know but less than 10 people'.

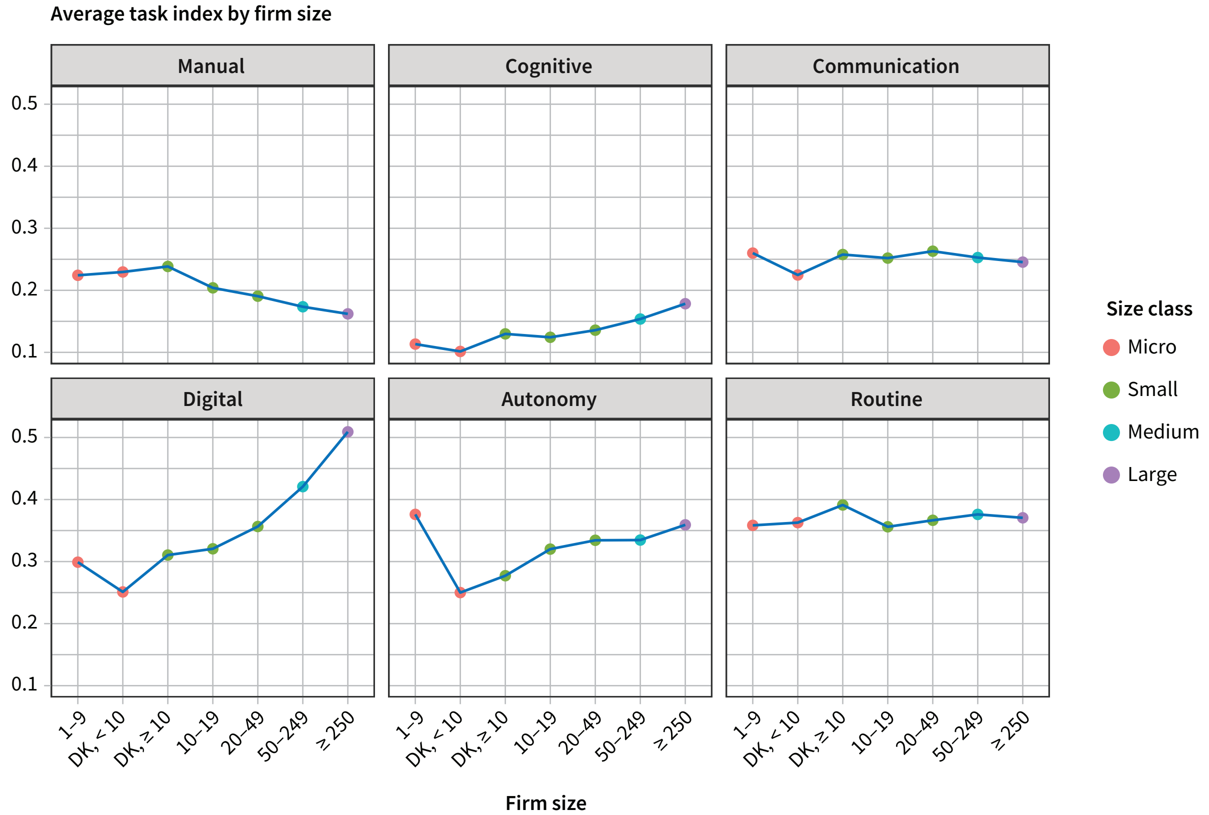
than in small ones. In microenterprises of less than 10 employees, around 40 % of respondents say that they never use digital devices at work, and only around 20 % say that they use them most or all of the time (16 % in those in the group DK, < 10, which have the lowest index value). In large firms of 250 employees or more, the figures are almost reversed: 40 % of employees use digital devices very frequently, and only 15.5 % say they never use them.

Nearly 4 in 10 employees working in enterprises of 10 people or fewer never use digital devices at work, compared to only 15 % working for enterprises of 250 people or more. The lack of adoption of ICT tools among small and medium-sized enterprises in the EU is well-documented and a cause of policy concern. Normally, this is attributed to a lack of digital skills within the workforce, but the task approach also emphasises the role or work organisation in adopting digital tools at work.

The autonomy on the order and content of tasks experienced by respondents also tends to increase with firm size, with the notable exception of the size class 1–9, which includes single-employee firms, who enjoy the largest autonomy overall. In the size class DK < 10, over 4 in 10 employees (40.2 %) say they have 'Little to no autonomy' in terms of either the order or content of their tasks. By contrast, among employees of firms of 250 people or more, only 24 % say the same.

Finally, in terms of routine, there is not really a discernible pattern in terms of firm size, because the two components of repetitiveness and standardisation vary in opposite directions, compensating each other. In terms of standardisation, among employees in the very smallest firms (1–9), 13.8 % say that their work is precisely described by strict procedures 'To a very large extent', whereas 21.4 % of those in employed in large firms (250 or more employees) say the same. The pattern is somewhat reversed for repetitiveness: 21.8 % of employees in the smallest firms say that their job repetitive 'To a very large extent' and only 17.2% of respondents in the largest firms say the same.

Figure 4: Average task indices for firms of different sizes



Note: *Each panel represents the how the corresponding average task index varies for firms of different size. The horizontal axis approximately ranks firm size as reported by respondents, including 'Do not know but less than 10 people' or 'Do not know but 10 people or more'. The size class 1–9 likely includes single-person firms, as it originally contained the exact number of employees, but is aggregated for confidentiality reasons. The vertical axis shows the average value of the task index, which can range 0 (lowest possible value) to 1 (highest possible value). The sample includes employees only, excluding the self-employed.*
Source: *2022 EU LFS ad hoc module on job skills.*

Overall, there is a clear and occasionally surprising variation in job tasks between smaller and larger firms, which stems from a combination of two factors: that firms of different sizes tend to operate in different sectors and that they adopt different forms of work organisation. In microenterprises and small firms, work tends to be more manual and less cognitive than in medium- or large-sized firms. This is especially notable considering that a greater share of employment in large firms is in the manufacturing sector. The difference in work organisation between firms of different sizes can also be seen in communication tasks: employees in larger firms spend more time communicating within the organisation, providing guidance or training, and less time communicating externally, compared to people working in smaller firms. Perhaps surprisingly, working in a larger organisation also seems to allow for more autonomy in the order and content of tasks than in smaller ones, with the exception of single-employee firms. Contrary to expectations, on average work in large enterprises is not more routine than in small ones: it tends to be somewhat more standardised but it is also less repetitive. Overall, work in large firms seems to involve higher cognitive skills, is less physically arduous, involves much higher use of digital devices, and allows for comparable or higher autonomy than smaller firms. Broadening the scope from individual to systemic differences, the next subsection looks at task differences between Member States.

Task differences between Member States

This section presents evidence on the variation of job tasks across the EU, both unconditionally and accounting for the different national employment structures.

One of the main advantages of the EU LFS module on job skills is that it allows for the comparison of the task profile of jobs across Member States. As discussed earlier, most other task surveys tend to cover the United States, or a single Member State. In the absence of Member State-specific data, the findings from these surveys are sometimes used to comment on the labour market structures outside the surveyed Member State, using conversion tables between different occupational classifications ('crosswalks') when needed. This assumes that any given occupation has the same task characteristics everywhere, a proposition that can rarely be tested empirically.

In principle, there can be significant differences in what the same job entails in different Member States, which can manifest both in forms of task content and in terms of work organisation. To take a striking example, a cook in a fine-dining restaurant in France and one in a fast-food chain in the United States may belong to the same occupation group, but they clearly prepare different meals (the task content) and use different cooking methods, such as more repetitiveness and standardisation in a fast-food restaurant (work organisation). We can expect some degree of variation in the nature of tasks of many different occupations across the EU, whether it is comparing the extent of manual work in agriculture between the Netherlands and Romania, the autonomy of secretaries in Germany and France or the use of digital devices by teachers in Estonia and Greece, for example.

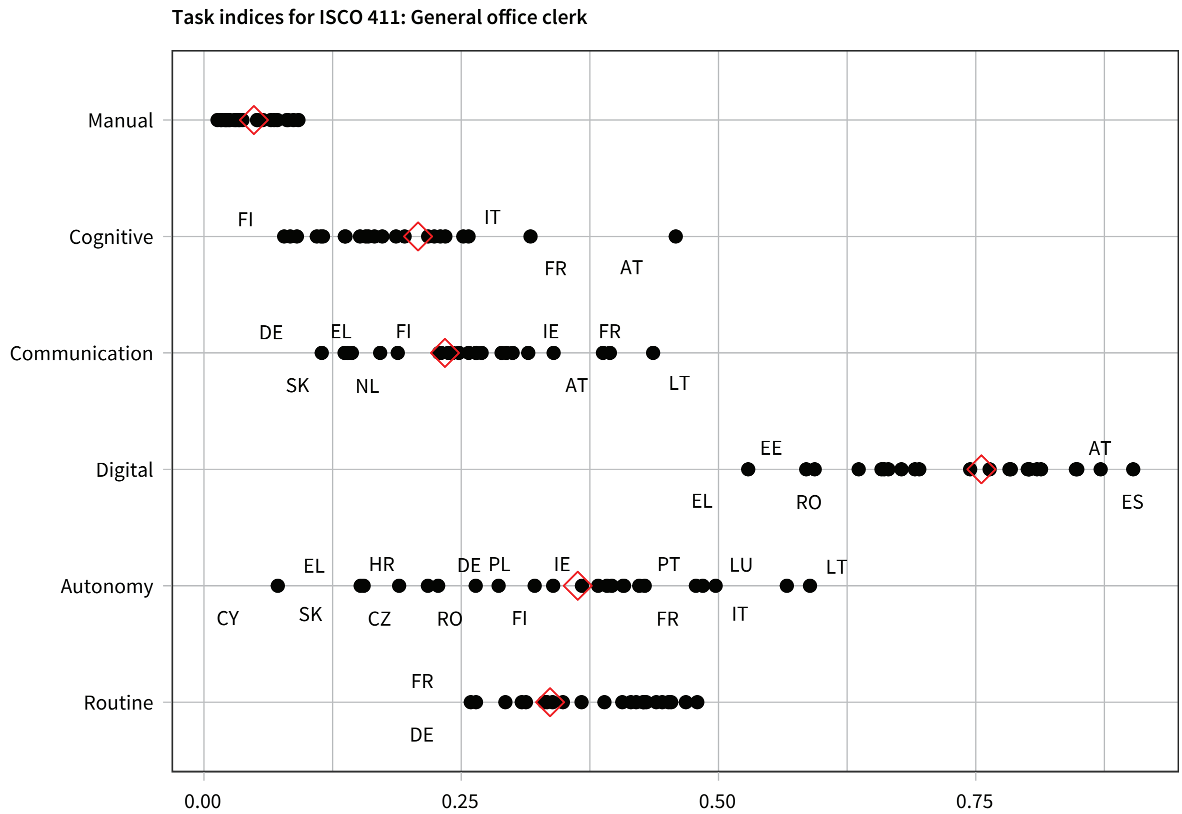
To illustrate just how similar or different the same occupation can be across different Member States, consider the case of ISCO 411: General office clerks. Figure 5 shows how the six task indices vary for this same occupation across Member States.

As the name implies, it is an office-based occupation and typically does not require much arduous physical activity: the share of respondents who say that they perform hard physical work at least half the working time (namely, who replied either 'Half of the working time or slightly more' or 'All or most of the working time') ranges quite narrowly, mostly in the range of 0 %–5 %, except for 7.8 % in Italy, or 6.6 % in France. Cognitive tasks such as reading, by contrast, are more frequent on average and vary more in absolute terms: in Austria, over 6 in 10 (60.8 %) clerks say they read at least half of their working time, considerably more than France, the second highest (44.6 %), while the lowest shares are in Finland (3.6 %) and Greece (5.5 %).

The most notable variation between Member States for this occupation concerns the use of digital devices and the degree of autonomy. Among the Member States with the highest digital task index for clerks are Spain, Austria, Sweden and the Netherlands, where over 90 % of office clerks say that they use digital devices at least half the working time. At the opposite end of the spectrum, in Greece, Estonia and Romania only two-thirds of clerks say the same.

The level of autonomy reported by clerks also varies significantly between Member States. The highest reported levels are in Lithuania and Luxembourg, where around 40 % of respondents say that they have a high level of control over the content of their tasks, whereas less than 4 % of their Greek and Cypriot colleagues said the same.

Figure 5: Member State variation of task indices for office clerks



Note: *Each dot represents one Member State, where the horizontal axis shows the average value of the task index, which can range 0 (lowest possible value) to 1 (highest possible value). The red diamonds denote the EU average. Member States include the EU-27, except for Bulgaria, Malta and Slovenia, which do not report occupations at the ISCO three-digit levels. For country codes, please refer to Table 16.*
Source: *2022 EU LFS ad hoc module on job skills.*

The case of office clerks shows that the same occupation can have substantial differences in its task profile between Member States. We may therefore wonder whether all occupations show the same type of Member State-level differences. Since Member States also differ somewhat in their occupational structure – the relative share of employment in each occupation, comparing the average task indices between Member States therefore requires controlling for differences in occupational structures. This can be achieved by averaging indices within and between occupations in the same Member States, using the methodology described in the box below. This correction allows us to see whether Member States have systematically higher or lower task values than expected, by comparing the observed average task indices of every Member State, to the task indices implied by their respective employment structure.

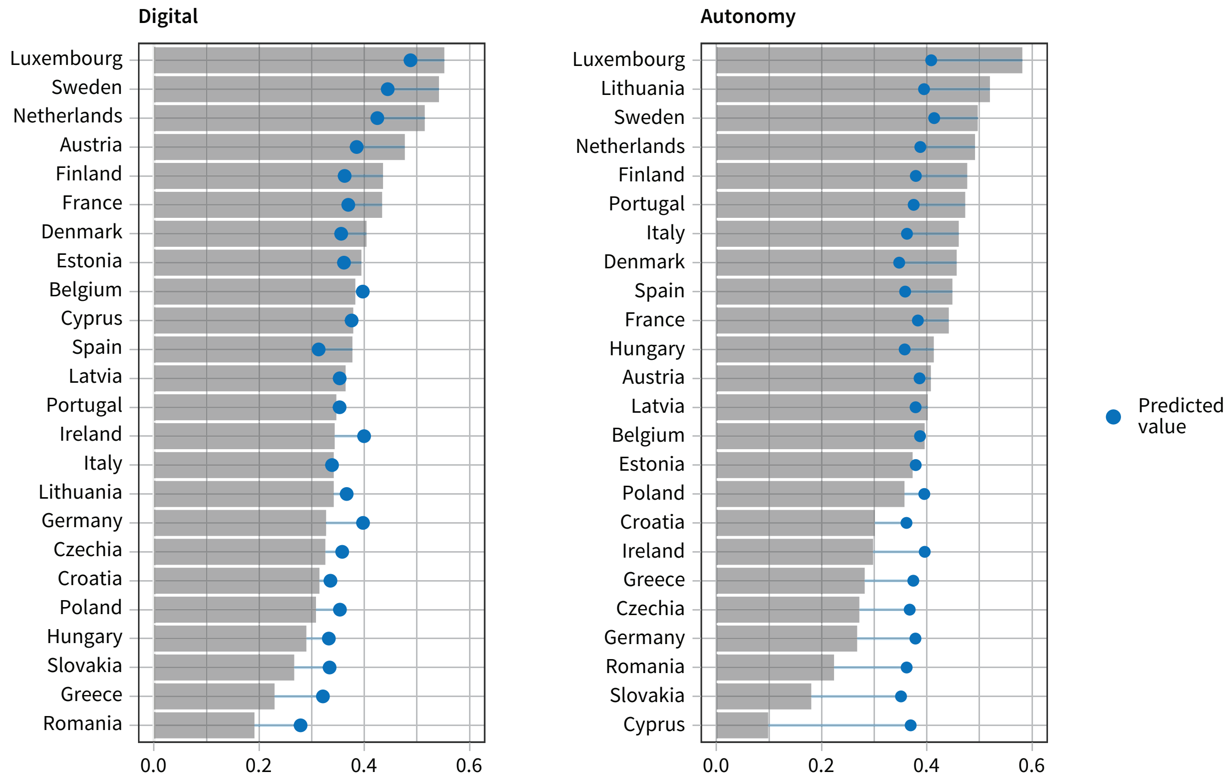
In Figure 7, we have plotted predicted values of task indices for each Member State on the horizontal axis and the observed values on the vertical axis. If the occupational structure perfectly predicted the actual indices, we would expect to see the points on the plot to tightly follow the 45-degree line (dashed diagonal line).

For every index except manual, Member States vary more than their occupational structure would predict, as shown by the estimated slope $\beta > 1$. This implies that there are systematic differences across Member States that cut across many occupations.

Consider digital tasks (see left panel of Figure 6): Sweden has the second-highest digital task index (after Luxembourg) and Romania the lowest. This is also what their occupational structures would predict, because Sweden has a proportionally larger share of digitally intensive occupations than Romania does. For example, ISCO 251: Software and applications developers and analysts account for 5.1 % of workers in Sweden, but only 1.2 % in Romania. However, the estimates show that the differences between Member States are even larger than predicted. This means that even occupations that normally have fewer digital tasks, such as nurses, are more likely to use digital devices in Sweden than in Romania. In Sweden, 60 % of nurses (ISCO 222) say they use digital devices at least half the working time, while in Romania only 12 % do.

Autonomy and routine vary significantly across Member States, to a greater extent than the occupational structure would predict. In fact, the low goodness-of-fit

Figure 6: Digital and autonomy indices – predicted and observed values by Member State



Note: *The bars represent the averages observed value of the digital and autonomy index in each Member State, and the dots represent the values predicted by that Member State's occupational structure. Task indices can range 0 (lowest possible value) to 1 (highest possible value). Member States include the EU-27, except for Bulgaria, Malta and Slovenia, which do not report occupations at the ISCO three-digit levels.*
Source: *2022 EU LFS ad hoc module on job skills.*

statistic R^2 shows that differences in occupational structures do not explain much variation at all in the observed values. The large variation in autonomy and routine between Member States is probably better explained by other factors that affect work organisation, including Member States' differences in systems of industrial relations, work cultures and management styles, rather than simple differences in occupational structure.

Box 1: Controlling for Member States' differences in occupational structure

To calculate the average values of the task indices for each Member State, we first calculate the average index for each occupation at the detailed occupation level (ISCO three-digits) separately for each Member State.

$$\text{index}_{c,o} = \frac{1}{n} \sum_{i|c,o} \text{index}_{i,c,o}$$

This varies for every Member State c and every ISCO-3 occupation o, where n is the number of observations in that occupation and Member State group.

For example, the average level of digital tasks in Belgium for 411: General office clerks is calculated as an average of all respondents in that occupation in Belgium.

Then we take a weighted average of the occupation-level indices, which gives us the Member State-level average

$$\text{index}_c = \sum_o w_{c,o}\text{index}_{c,o}$$

where $w_{c,o}$ is the share of people employed in occupation o in Member State c, among all people employed in the Member State, such that $\sum_o w_{c,o} = 1$.

For example, to get an average level of digital tasks in Belgium, we will take the average that we calculated earlier for 411: General office clerks and multiply it by its occupational share in the Belgian workforce, which is approximately 7 %, and add all the averages for other occupations multiplied by their own weights.

We predict the Member State-level averages from the occupational structure of the Member State by first calculating the occupation-level averages at ISCO-3 level.

We first average all indices for occupation o across all Member States, giving equal weight to each Member State, which provides a more robust estimate of tasks at the occupation level

$$\overline{\text{index}}_o = \frac{1}{N}\sum_c \text{index}_{\,c,o}$$

where N is the number of Member States that have occupation o – in practice, this is at most 24, since three of the EU-27 do not report occupation codes at the ISCO three-digit level.

For example, to calculate the average digital index for ISCO 411: General office clerks for the whole of the EU, we will sum up all of the Member States' estimates for that occupation and divide the total by the number of Member States (in this case, 24 Member States).

Finally, we estimate the predicted index for each Member State based on their occupational structure by using a weighted average across all occupations using the predicted occupation-level indices.

$$\overline{\text{index}}_c = \sum_o w_{c,o}\overline{\text{index}}_o$$

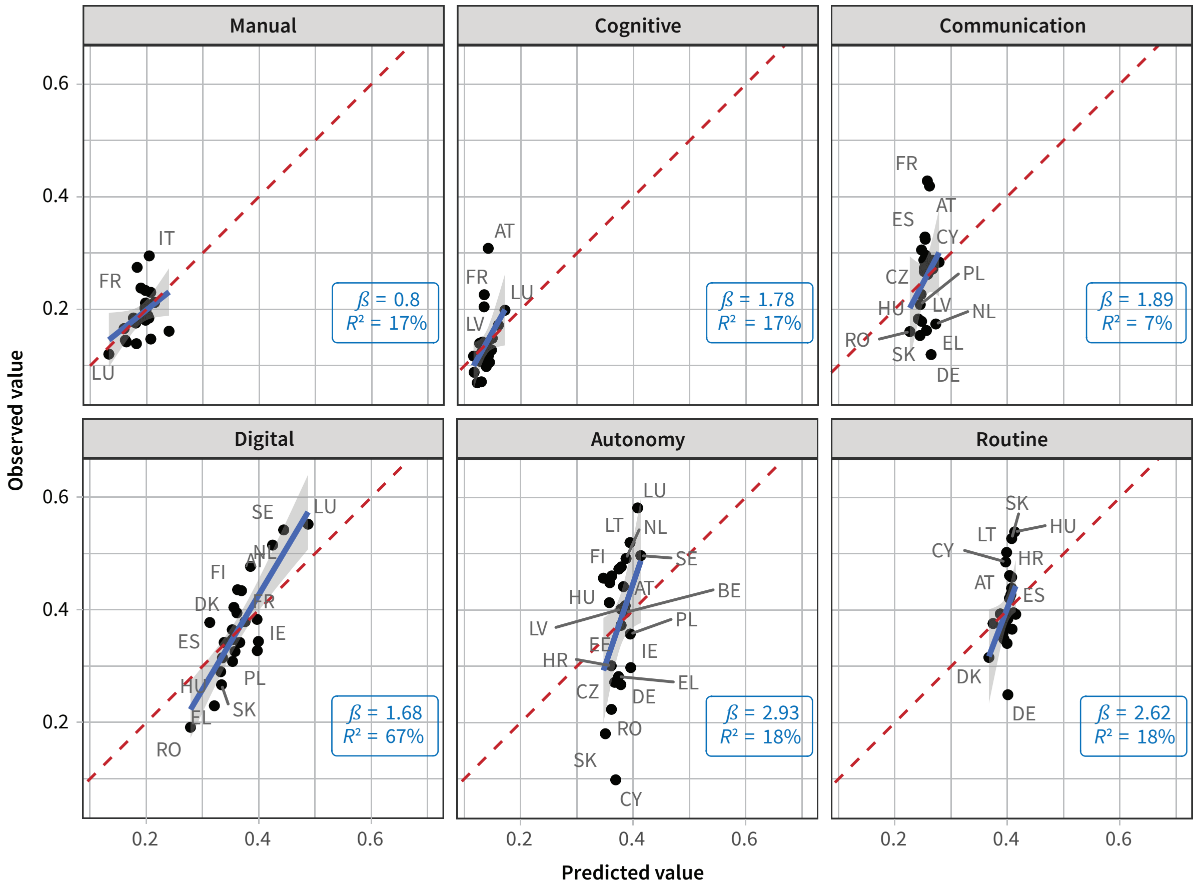
For example, to predict the level of the digital task index for Belgium, we will take the average digital task indices for different occupations, as estimated using all Member States, and weight those using occupational weights of Belgium.

Hence, $\overline{\text{index}}_c$ provides an estimate of the predicted index per Member State c based on its occupational structure ($w_{c,o}$).

These findings show just how different the same job can be between different Member States. Notably, the use of digital devices varies substantially between Member States, and not just because Member States have a different mix of jobs, such as a larger number of software developers in some, but because some Member States are more likely to use digital devices in every occupation. The fact that the indices for digital use, autonomy and routine vary substantially more than expected between Member States also illustrates a larger point: how work is organised in different firms or Member States matters. For example, whether clerks or nurses use digital devices does not necessarily depend on their skills, but rather on whether their firms integrate digital devices into their work. Likewise, we can speculate that national differences in institutions and culture can affect forms of work organisation, which results in workers experiencing different levels of autonomy or routine across Member States. The precise mechanisms by which this happens are beyond the scope of the survey but could be of interest for future research.

Having established how job tasks vary across a number of demographic and structural dimensions, the next section uses the task approach to comment on the structural changes of the EU economy over the past decade.

Figure 7: Task indices by Member State – predicted and observed values



Note: *Each panel represents the average task indices for Member States observed in the data (vertical axis) and predicted by their occupational structure (horizontal axis). Task indices can range from 0 (lowest possible value) to 1 (highest possible value). The dashed 45-degree line corresponds to the reference case where the observed value is equal to the predicted value. The blue line and shaded area show the best fit in a linear model, whose slope coefficient β and goodness-of-fit* R^2 *value are shown in the box of each panel. Member States include the EU-27, except for Bulgaria, Malta and Slovenia, which do not report occupations at the ISCO three-digit level. For country codes, please refer to Table 16.*
Source: *2022 EU LFS ad hoc module on job skills.*

3 Recent changes in employment and task composition of the EU economy

Table 7: Value-added, employment and productivity change in sector groups, 2011–2020

	2011			2020		
	Value added (Billion EUR)	People employed (Million)	Productivity (*) (Thousand EUR/person)	Value added (Billion EUR)	People employed (Million)	Productivity (*) (Thousand EUR/person)
Agriculture/extractive	248	10.1	24.6	239	8.3	28.8
Construction	594	13.5	44.0	562	12.6	44.6
Manufacturing/utilities	2 102	33.5	62.7	2 242	34.8	64.4
Mainly public services	2 037	45.0	45.3	2 099	49.1	42.7
Mainly private services	5 633	80.4	70.1	6 094	85.6	71.2
Total	**10 614**	**182.5**		**11 236**	**190.4**	

(*) *Value added/employee.*
Sources: *EU LFS for employment (employees aged 15–64 only), and the EU KLEMS: capital, labour, energy, materials and service project for value-added by sector group. Value-added expressed in 2015 Euro value. Most recent data is from 2020.*

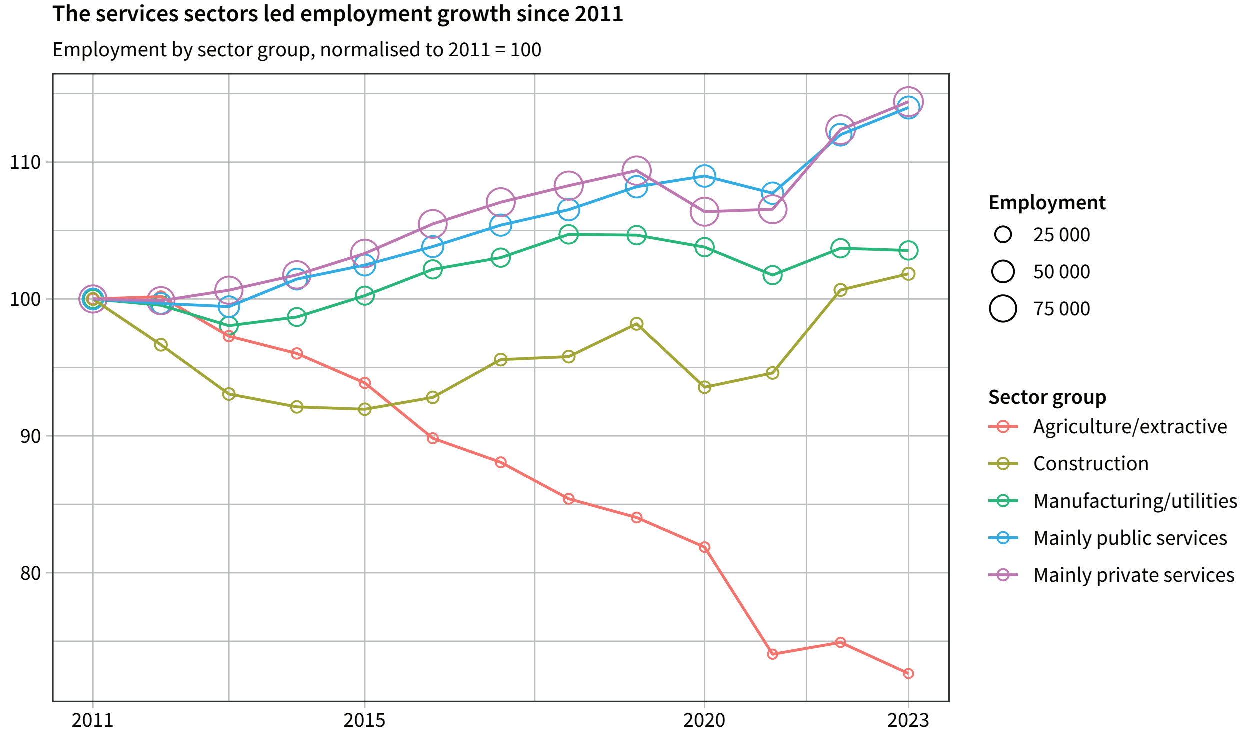
The structures of the EU-27 economies have gradually changed over the last decade, with an ever-increasing share of employment and value-added in both public and private services (6).

In 2011, based on EU LFS data, the service sector – including mainly private and mainly public services – accounted for the largest shares of EU employment. Mainly private services employed for 80.4 million working-age people (44.1 % of total EU-27 working-age employment) and mainly public services employed 45 million (24.7 %). The manufacturing sector employed 33.5 million people (18.4 %), construction 13.5 (7.4 %), and the agriculture and extractive sectors accounted for the smallest share of employment with 10.1 million, or 5.5 % of the EU-27 in 2011.

Since then, employment in services has grown even further (see Figure 8): both public and private services employed 14 % more people in 2023 than they did in 2011, creating about 10.6 million jobs in private services and 6.3 million in public services. Both sectors experienced a decline in employment during the COVID-19 pandemic in 2020 and 2021, but have since recovered quickly, and continued to grow sharply in 2022 and 2023. Employment in manufacturing, by comparison, has grown only by 4 %, adding 1.2 million jobs. The construction sector has gone through two cycles of decline and growth in employment, and has been growing faster since 2020, with 200 000 more jobs in 2023 than in 2011. The agriculture sector stands out as having continuously declined, having lost 2.8 million jobs, or about a third of its initial employment, since the beginning of the period.

(6) This sectoral classification is based on Eurofound (2025), and is shown in Table 19, 'Sector grouping', in Annex 2.

Figure 8: Changes in employment by sector group



Note: *The lines show relative employment trends for five groups of sectors of economic activity. Relative changes are indexed to 100 in 2011. The size of each bubble represents the total employment in the sector group in each year.*
Source: *EU LFS 2011–2023.*

These structural employment trends imply a change in the nature of work in the EU. Table 8 shows that these sector groups have substantially different task profiles. When comparing to employment trends in Figure 8, it is striking to see how the sectors shrinking in employment (agriculture and extractive sector), broadly stagnating (construction) or modestly growing (manufacturing and utilities) are those with relatively high levels of manual tasks, lower levels of cognitive tasks, communication tasks and digitisation. By contrast, the fast-growing services sector are less manual, more cognitive, involves more communication and use of digital tools. Interestingly, there is no clear pattern in terms of tasks' indicators of job quality like autonomy and routine: the two sectors with the highest levels of autonomy are agriculture/extractive and mainly private services, and these have experienced completely opposite employment trends over the decade.

Table 8: Average task indices by sector group

Sector group	Manual	Cognitive	Communication	Digital	Autonomy	Routine
Agriculture/extractive	0.326	0.062	0.123	0.094	0.497	0.351
Construction	0.361	0.127	0.194	0.192	0.386	0.371
Manufacturing/utilities	0.245	0.134	0.178	0.321	0.311	0.389
Mainly public services	0.167	0.147	0.323	0.390	0.388	0.376
Mainly private services	0.168	0.153	0.260	0.438	0.408	0.351

Source: *Own elaboration from the 2022 EU LFS ad hoc module on job skills. Indices can range from 0 (lowest) to 1 (highest).*

These differences in task content between growing and shrinking sectors may reflect a structural change over the period in terms of employment at the job level, that is, for combinations of occupations in each sector groups. Table 9 shows the 10 jobs that have grown most in employment terms over the period 2011–2023, while Table 10 shows the jobs that have decreased the most.

Growing and shrinking jobs

Some of the largest absolute changes occurred in private and public services, which to some extent is to be expected, a most employment since 2011 has been in these sectors. Nevertheless, it is interesting to note how large some of these changes have been, in both absolute and relative terms. Among the 10 jobs with the largest increases, 6 out of 10 of them were high-skilled professional occupations (ISCO major group 2), such as 251: Software developers and analysts, which saw the largest absolute increase in employment, by 1.6 million, a 117 % increase between over 11 years. Next were 243: Sales, marketing and Public relations professionals, which increased by 1.2 million (+ 179 %). Other fast-growing occupations in the private services included professional occupations in administration and finance, but also occupations relating to transport and logistics. Within the mainly private services, the

Table 9: The 10 fastest-growing jobs between 2011 and 2022

		Employment (thousands)		Employment change 2011–2022	
Sector group	**ISCO occupation**	**2011**	**2022**	**Absolute**	**Relative**
M. private services (*)	251: Software and applications developers and analysts	1 373	2 979	1 606	117 %
M. private services	243: Sales, marketing and public relations professionals	675	1 879	1 204	179 %
M. public services	411: General office clerks	1 122	2 157	1 034	92 %
M. public services	234: Primary school and early childhood teachers	3 050	4 055	1 005	33 %
M. private services	242: Administration professionals	846	1 598	752	89 %
M. private services	241: Finance professionals	1 204	1 946	742	62 %
M. public services	263: Social and religious professionals	1 037	1 743	706	68 %
M. public services	325: Other health associate professionals	1 074	1 726	652	61 %
M. private services	933: Transport and storage labourers	1 197	1 833	636	53 %
M. private services	432: Material recording and transport clerks	1 713	2 230	517	30 %

(*) *Mainly private services.*
Source: *EU LFS, 2011–2022.*

Table 10: The 10 fastest-shrinking jobs between 2011 and 2022

		Employment (thousands)		Employment change 2011–2022	
Sector group	**ISCO occupation**	**2011**	**2022**	**Absolute**	**Relative**
Agriculture/extractive	613: Mixed crop and animal producers	3 414	1 763	– 1 651	– 48 %
M. public services	441: Other clerical support workers	833	312	– 521	– 63 %
M. private services	522: Shop salespersons	9 819	9 401	– 418	– 4 %
M. private services	911: Domestic, hotel and office cleaners and helpers	4 555	4 158	– 397	– 9 %
M. private services	441: Other clerical support workers	1 495	1 112	– 383	– 26 %
M. private services	421: Tellers, money collectors and related clerks	1 181	807	– 374	– 32 %
M. public services	334: Administrative and specialized secretaries	1 585	1 232	– 354	– 22 %
M. private services	513: Waiters and bartenders	2 641	2 329	– 312	– 12 %
Manufacturing/utilities	722: Blacksmiths, toolmakers and related trades workers	2 040	1 747	– 293	– 14 %
Agriculture/extractive	633: Subsistence mixed crop and livestock farmers	293	9	– 284	– 97 %

Source: *EU LFS, 2011–2022.*

largest increase appears to be in clerical jobs (411: General office clerks increased by one million or + 93 %), though this increase may be spurious, and may partially result from the reclassification within the survey of other clerical occupations, such as secretaries as shown in Table 9 – 441: Other clerical support workers, which decreased by half a million over the time span, and 334: Administrative and specialized secretaries, which shrank by 353 000. The ranks of 234: Primary school and early childhood teachers increased by one million employees (or by about a third). Other increases in public services occurred in health and social care, by around 68 %). The biggest fall in employment, by contrast, happened in agriculture: 613: Mixed crop and animal producers fell by 1.6 million, or nearly one-half over 11 years. Other large drops in employment were registered among 522: Shop salespersons, which fell by 417 000, though that amounts to a relatively modest 4 % decrease. Aside from apparent falls in clerical occupations (which may stem from reclassification), most decreases in employment concerned occupations requiring middle-to-low levels of qualifications in the private services, such as 911: Domestic, hotel and office cleaners and helpers, 421: Tellers, money collectors and related clerks, 513: Waiters and bartenders. Other fast-shrinking jobs were in manufacturing 722: Blacksmiths, toolmakers and related trades workers, and agriculture 633: Subsistence mixed crop and livestock farmers.

The picture that emerges is one of ever-increasing employment in the service sector. In the mainly private services, this involves marked growth in high-skilled professional occupations in ICT, sales and finance, and office-based jobs more generally, and to a lesser extent transport and logistics. The sector also saw some of the largest absolute falls in employment, mostly among mid-to-low skilled occupations.

Employment growth in the mainly public services appeared somewhat more diversified, spanning early childhood education, to health and social care. Some of the fastest-declining jobs overall were in agriculture, which is broadly in line with the decline in agricultural employment over the period (see Figure 8), while, remarkably, total value-added remained essentially the same over a similar period (see Table 7).

Overall, these shifts in employment result in a change in the nature of work in the EU. The next section explores how the jobs in sectors experiencing structural change involve different tasks – and may require different skills – than those in declining sectors.

The rise of cognitive and digital work

The changing nature of work over this period is most evident when looking at the trajectories over time of different groups of occupations, ranked based on their relative task intensity.

For a simple illustration, we calculate the average task indices for all the 127 ISCO three-digit occupations observed in the 2022 EU LFS ad hoc module, for each of the six task dimensions: manual, cognitive, communication, digital, autonomy and routine. We then rank occupations along each of the six task dimensions, from the highest to lowest value of the task index. Occupations with values above or equal to the median occupations (that is, the upper half of the distribution) are classified as ‘high’ in that dimension, and those with lower value (the bottom half) are classified as ‘low’. Table 20 shows an excerpt of the rankings for each task dimension, showing the five occupations with the highest value of each task index, the median occupation and the five occupations with lowest values. For example, some of the occupations with the highest manual task contents are in the building trades: 712: Building finishers and related trades workers, 711: Building frame and related trades workers, 713: Painters, building structure cleaners and related trades, along with 622: Fishery workers, hunters and trappers and 514: Hairdressers, beauticians and related workers. The occupations with the lowest intensity of manual tasks are professional and managerial: 212: Mathematicians, actuaries and statisticians, 261: Legal professionals, 241: Finance professionals, 242: Administration professionals and 121: Business services and administration managers. The median occupation in terms of manual task content (that is, the one that divides the ranking into two equally sized groups) is 312: Mining, manufacturing and construction supervisors: a supervisory position in an otherwise manually intensive sector.

This simple classification of occupations as being (relatively) high or low in each task dimension allows us to broadly describe changes in employment structure since 2011 (similar to Autor et al. (2003), or Cirillo et al. (2021)). This is the first year the current version of the ISCO-08 classification was implemented into the EU LFS, which allows us to compare employment levels for the same occupations over time.

It is important to note that the task content of occupations was measured only once, in 2022. The analysis only reflects changes in the employment levels of different occupations, not in the task content of the occupations themselves. While some task dimensions within occupations have likely changed little over a decade – manual, cognitive, communication – others like autonomy and routine may have, and the use of digital technology has certainly expanded to more occupations and increased in frequency from 2011 to 2022. Nevertheless, this type of analysis is useful to understand the employment changes that have led to the current labour market structure.

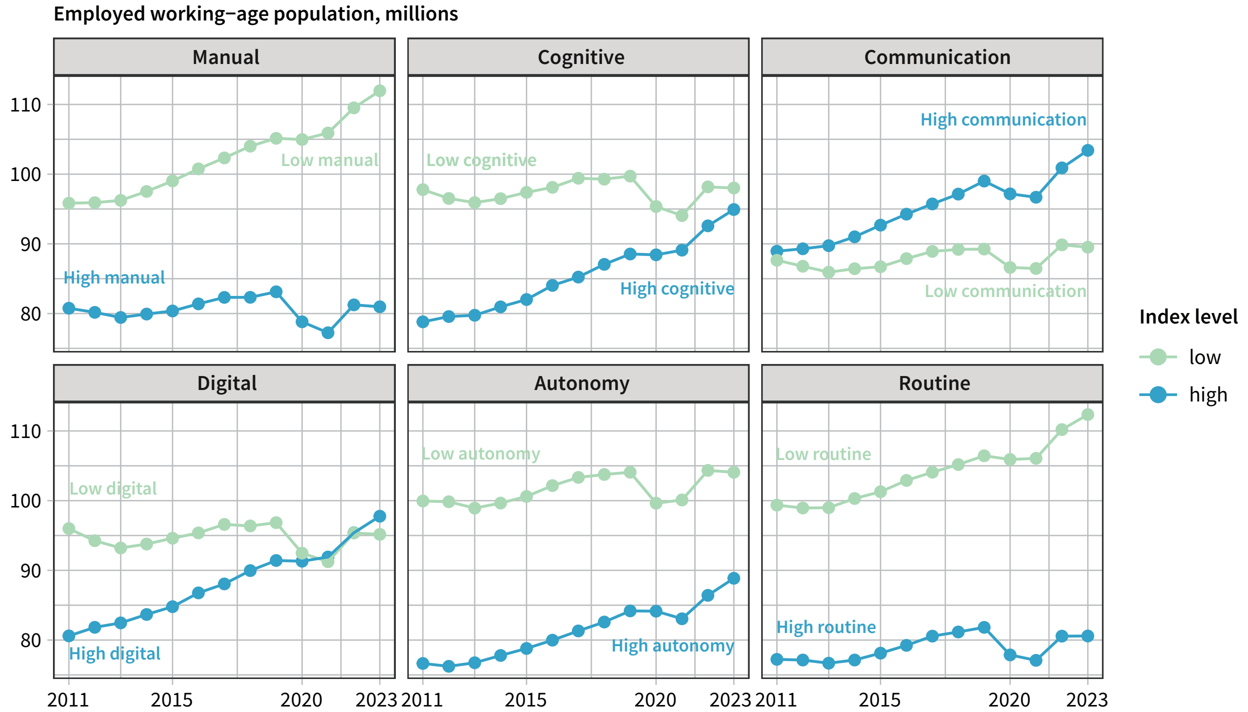
Indeed, the changing nature of work in the EU-27 is quite apparent from the trends in different task dimensions shown in Figure 9. The top-left panel shows the trajectories of employment in highly manual occupations, which has mostly remained stable at around 80.5 million people, whereas occupations with a low manual component have grown considerably, from 95.8 million in 2011, to over 111 million in 2023. This has gone hand-in-hand with the growth of highly cognitive occupations, which grew by 16 million jobs over the same period, while occupations with fewer cognitive tasks remained relatively constant, adding only 1.6 million jobs to the 97.7 million in 2011. Employment in these occupations accounts for a small majority of total employment, but if the current trend persists, employment in highly-cognitive occupations is set to overtake it in the following years. In 2011, employment was evenly split between occupations with high levels of communication tasks and those with lower levels. Since then, there has been a sustained growth in employment with high levels of communication, while the rest has remained constant. The rising employment in digitally intensive occupations is especially notable. It has been growing steadily throughout the time period, and in 2020 overtook employment in less digitally intensive occupations. In terms of methods of work and proxies for job quality, employment in high-autonomy jobs has risen steadily, while that in low-autonomy jobs grew only slightly. Conversely, employment in high-routine occupations grew little, while most of the growth was in low-routine occupations.

These trends collectively describe the changing composition of the EU workforce, which is increasingly carrying out higher-skilled, more digital, more communicative work, benefiting from more job autonomy and lower levels of routine at work. The next section examines whether the growth in high-skilled employment may have exceeded the supply of skilled workers, leading to skill shortages.

Labour and skill shortages – a task perspective

Data on job tasks can help better understand the nature of labour shortages, by comparing the task profiles of occupations experiencing shortages to the rest of the workforce. Although the EU LFS module on job skills covers a somewhat limited range of task types, these can potentially help distinguish between shortages attributable to cognitive skills and those attributable to working conditions. In particular, the frequency of cognitive and digital tasks can act as proxies of higher

Figure 9: Changing task content of EU-27 employment

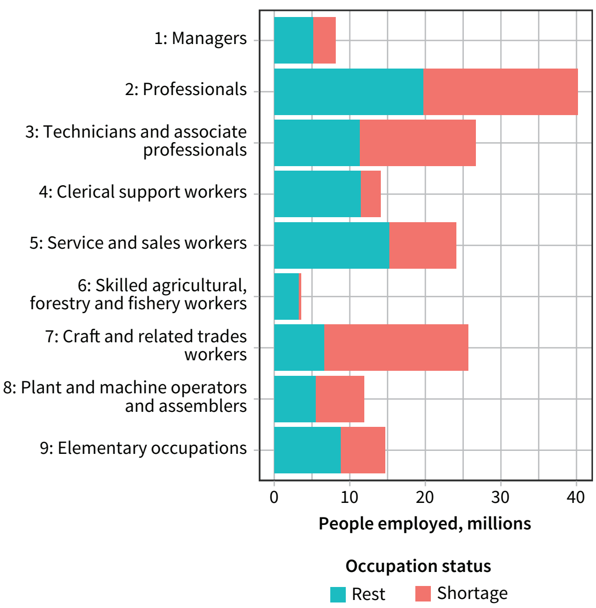


Source: *EU LFS 2011–2023, 2022 EU LFS module on job skills.*

educational requirements. The degree of autonomy and routine can instead proxy for job quality and working conditions. Such proxies are clearly reductive measurements of the diversity of both skill requirements and working conditions, but we assume that they capture some relevant aspects of both.

The European Labour Authority (ELA) and the European Employment Services (EURES) publish annual reports on the state of labour shortages in the EU-27, plus Norway and Switzerland. For 2022, the report gathered information from EURES National Coordination Offices in Member States on labour market imbalances. These included, for each country, a list of detailed occupations that were experiencing shortages, and, in most of them, which occupations were experiencing surpluses (European Labour Authority and Fondazione Giacomo Brodolini, 2023).

Figure 10: Employment in occupations affected by labour shortages by 2022, millions of people



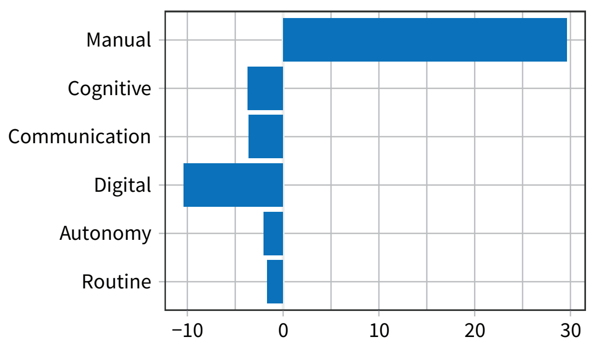
Source: *2022 EU LFS ad hoc module on job skills.*

To understand the scale and scope of labour shortages, consider the number of people employed in occupations that experienced some degree of labour shortages. In 2022, around 46 million people (or 37 % of total employment) were employed in occupations that were affected by labour shortages at least to some degree. This does not represent the total number of people that would need to be added to the workforce to fill the shortages, but the scale of incumbent employment in the affected occupations.

Labour shortages affect every major occupation group to different extents. Figure 10 shows the number of people employed in ISCO three-digit occupations affected by shortages in the EU in 2022, compared to the rest of employment in unaffected occupations. In terms of total employment, the occupation major groups the most affected were ISCO 2: Professional and 3: Technicians and associate professionals. In 2022, they respectively employed 11.1 million people and 9.5 million people in occupations that experienced some degree of shortage. Relative to total employment in the group, the worst affected were ISCO 7: Craft and trade workers (employment in shortage occupations was 55 % of total), 3: Technicians and associate professionals (48 %) and 8: Plant and machine operators (45 %).

Shortage occupations can vary substantially in terms of task profiles, and these may help explain why the shortages are occurring in the first place. Figure 11 compares the task indices of shortage occupations identified in each Member State by ELA and EURES, with the rest of the workforce, including occupations experiencing surpluses, where reported. On average, shortage occupations seem to feature substantially more frequent manual tasks, compared to the other occupations: the difference between the task indices for the two groups is about 30 %. They also make notably less use of digital devices (– 10.4 %) and have somewhat less frequent cognitive and communication tasks (– 3.7 % and – 3.6 %, respectively). In terms of work organisation and job quality, the picture is mixed: shortage occupations also tend to report less autonomy (– 2 %), which would make them less desirable, but also less routine (– 1.7).

Figure 11: Task indices of shortage occupations, relative to other occupations, % difference



Note: *The bars measure the average relative difference between the task indices of Member State-specific shortage occupations in the EU compared to all other occupations.*
Source: *Elaboration from 2022 EU LFS module on job skills and 2022 ELA–EURES list of shortage occupations in the EU27.*

As specific examples, consider the 10 largest occupations in terms of employment, among those experiencing shortages, shown in Table 11.

Among the 10 largest occupations experiencing shortages, we can distinguish two distinct groups. The first group includes six occupations, mostly in the range

Table 11: Task profiles of shortage occupations, by current employment in the EU-27

	Current EU-27 employment (thousands)	Manual	Cognitive	Communication	Digital	Autonomy	Routine
EU average		**0.205**	**0.138**	**0.250**	**0.360**	**0.377**	**0.365**
532: Personal care workers in health services	2 294	0.330	0.061	0.281	0.133	0.319	0.462
911: Domestic, hotel and office cleaners and helpers	2 039	0.292	0.014	0.112	0.021	0.318	0.376
723: Machinery mechanics and repairers	1 866	0.422	0.103	0.178	0.148	0.337	0.335
214: Engineering professionals (excluding electrotechnology)	1 589	0.078	0.297	0.253	0.683	0.498	0.290
311: Physical and engineering science technicians	1 574	0.169	0.221	0.213	0.522	0.392	0.373
322: Nursing and midwifery associate professionals	1 556	0.347	0.111	0.271	0.230	0.250	0.464
833: Heavy truck and bus drivers	1 526	0.210	0.044	0.145	0.067	0.173	0.407
251: Software and applications developers and analysts	1 522	0.039	0.254	0.215	0.923	0.535	0.238
711: Building frame and related trades workers	1 368	0.468	0.075	0.164	0.044	0.345	0.389
242: Administration professionals	1 245	0.036	0.230	0.288	0.759	0.531	0.280

Source: *2022 EU LFS ad hoc module on job skills.*

of so-called middle to low-skilled (ISCO 4–9), and involve more manual tasks, and less cognitive and digital tasks. They also report lower-than-average autonomy and higher routine. This group encompasses ISCO 532: Care workers in health services, 911: Domestic, hotel and office cleaners and helpers, 322: Nursing and midwifery associate professionals (which belongs to the high-skilled occupation group of associate professionals), 711: Building frame and related trades workers and 723: Machinery mechanics and repairers, except that this last occupation reports slightly below-average routine.

The second group includes so-called skilled occupations (ISCO 1–3) and has the opposite task profile: low in manual tasks, high in cognitive and digital tasks, reporting high autonomy and low routine, and includes ISCO 214: Engineering professionals, 251: Software and applications developers and analysts, 242: Administration professionals and 311: Physical and engineering science technicians, though they report slightly above-average routine.

Notice that communication tasks do not seem to correlate much with other task indices. For example, jobs involving high levels of communication can involve either high levels of manual tasks, such as 532: Personal care workers in health services, or very low levels, like 242: Administration professionals.

On aggregate, the biggest difference between occupations experiencing shortages and the rest is that they are substantially less manual, less digital. However, there appear to be no major differences in autonomy and routine in the aggregate, which means that working conditions are not always the reason for shortages either. This average picture can overlook specific cases where skill shortages do exist, or where working conditions play a role, such as in the healthcare sector.

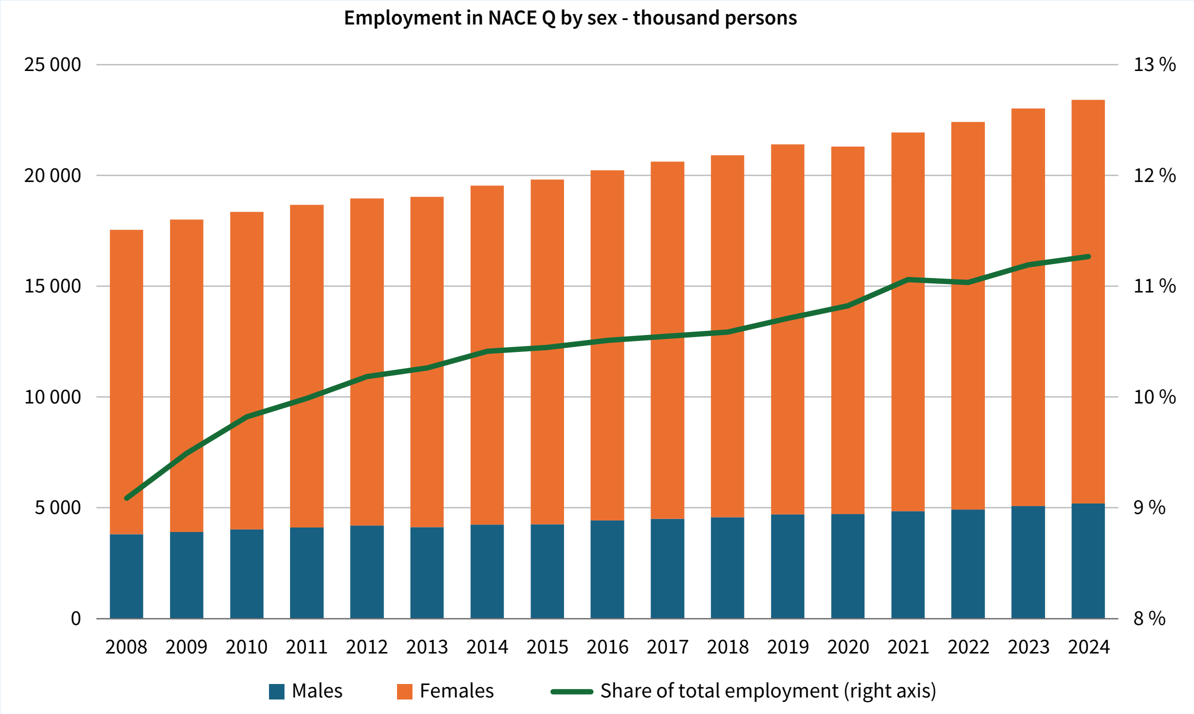
Box 2: A case of labour shortage – focus on the health and care sector

Human health and social work activities (statistical classification of economic activities in the European Community, section Q (NACE Q)) is among the sectors that grew at a greater rate than general employment over more than a decade (see Figure 12). It is one of the key sectors for ageing European societies; the process of demographic ageing is likely to imply the growing needs for health and care services for the elderly. The sector also accounts for a substantial share of national expenditure in terms of the share of the gross domestic product. This expenditure has also grown over time and in particular was increased during the COVID-19 pandemic (Eurofound, 2023a).

With regard to subsectors in NACE Q as a whole, it is notable that employment in the subsector of ‘Social work activities without accommodation’ expanded most – increasing from 20 % of workers in NACE Q in 2008 to nearly 24 % in 2024. It has grown relatively more than ‘Residential care services and human health activities’.

The growth of employment in the EU in recent years was by and large accounted for by the rising participation in the labour market of women and older workers. It was also reflected in the health and social work sector. This section, which was known for its high share of women workers, increased this proportion even further (see Figure 12).

Figure 12: Employment in human health and social work activities, EU-27



Source: *EU LFS, 2008–2024.*

According to the European Jobs Monitor (Eurofound, 2025), the overall trend in the NACE Q section over the last decades has been one of upgrading – the newly created jobs emerged in the middle and on the better paid side of the job distribution rather than in the low-paid segment. In principle, this followed the overall trend of the structural change in the EU's labour market where over the period of the last three decades, employment growth has been strongest in well-paid, top-quintile jobs.

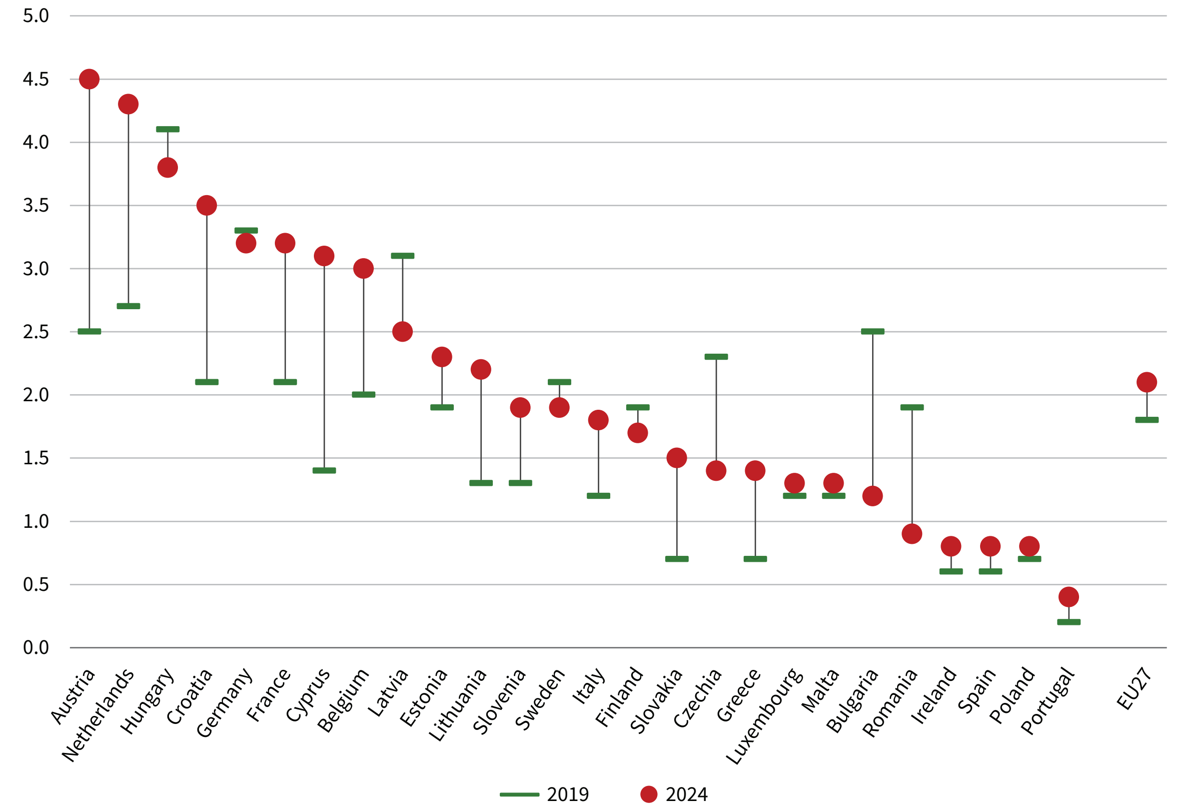
At the same time, compared to the entire economy, a substantial proportion of jobs in the sector do not stand out in terms of wages. The sector is also known for several features of the challenging working conditions, particularly in its most numerous occupations involving nursing and care. The jobs in health and care services involve higher than average manual work and exposure to infectious substances and the psychosocial risks involving exposure to adverse social behaviour (see Eurofound, 2020, 2023a, 2023b).

The issues around job quality could be one of the factors contributing to the persistent labour shortages in the sector. The vacancy rates in the sector increased from 1.8 % in 2019 to 2.1 % in 2024 in the EU on average (Figure 13). In particular, nurses are in short supply in majority of Member States (hence the relevance of the EU/WHO action plan for nurses (7)). The demand for general practitioners and issues around long-term care workers are also known issues in a number of Member States (Table 12).

Addressing the acute labour shortages and securing the long-term sustainability of the sector and its workforce are pressing political priorities. Understanding the prevailing tasks in the jobs of this sector could shed additional light on the challenges and prospects for its workforce.

(7) European Commission, 'Commission supports action across Europe to attract and retain nurses', European Commission website, 2 September 2024, https://health.ec.europa.eu/latest-updates/commission-supports-action-across-europe-attract-and-retain-nurses-2024-09-02_en.

Figure 13: Vacancy rate in the human health and social work sector, EU-27, 2019–2024 (%)



Source: *European Commission: Eurostat, 'Job vacancy statistics by NACE Rev. 2 activity – quarterly data (from 2001 onwards)', 16 May 2025,* https://doi.org/10.2908/JVS_Q_NACE2*, annual average of quarterly figures. EU-27 excludes Denmark.*

Table 12: Member States reporting shortages and surpluses for selected occupations in NACE Q – Human health and social work activities

Occupation (ISCO three-digit)	Member States reporting shortages	Member States reporting surpluses
222: Nursing professionals	18	0
221: Generalist medical practitioners	14	0
226: Physiotherapists	11	0
532: Health care assistants	11	1
221: Specialist medical practitioners	10	0
322: Nursing associate professionals	9	0
532: Home-based personal care workers	8	2
222: Midwifery professionals	7	0
226: Dentists	7	0

Source: *2022 ELA/EURES data on labour shortages.*

Table 13: Task indices for largest occupations in NACE Q – human health and social work activities

Occupation group	Employment share in sector (%)	Manual	Cognitive	Communication	Digital	Autonomy	Routine
EU average		0.205	0.138	0.250	0.360	0.377	0.365
Sector average		0.247	0.110	0.298	0.294	0.356	0.426
532: Personal care workers in health services	28.3	0.330	0.061	0.281	0.133	0.319	0.462
322: Nursing and midwifery associate professionals	17.1	0.347	0.111	0.271	0.230	0.250	0.464
325: Other health associate professionals	13.3	0.231	0.114	0.254	0.322	0.307	0.402
226: Other health professionals	12.4	0.286	0.136	0.345	0.325	0.449	0.425
221: Medical doctors	10.4	0.178	0.165	0.350	0.435	0.419	0.454
222: Nursing and midwifery professionals	10.1	0.271	0.142	0.389	0.326	0.331	0.532
321: Medical and pharmaceutical technicians	6.3	0.236	0.172	0.303	0.459	0.279	0.518
225: Veterinarians	1.0	0.300	0.164	0.329	0.303	0.514	0.393

Note: *Indices can range [0-1], where higher value corresponds to more time spent on the task, a larger extent of routine or standardisation, or a higher level of autonomy.*
Source: *2022 EU LFS module on job skills.*

The analysis of task profiles of the occupations in the sector confirms the challenging nature of certain jobs in the sector. Nurses (associate professionals) and carers (personal care workers), who make up nearly half (45 %) of the sector's workforce, carry considerably higher than average burden of manual work, and have lower levels of communication and cognitive tasks in their work. High routinisation is also a known issue for job quality in many healthcare occupations. Nursing and midwifery professionals (ISCO 222) report the third-highest level of routine overall, just below transport traffic controller (see Table 20 in Annex 2): three-quarters (75 %) report that their job is precisely described by strict procedures to 'A large or very large extent', and 53 % say that their job is repetitive to the same extent. The level of autonomy reported by healthcare professionals follows occupational hierarchies in the clinical environment: one of the highest levels is reported by medical doctors (ISCO 221), 24 % of which report having a high degree of autonomy in setting the order and content of their tasks. Only 15.1 % of Nursing and midwifery professionals (ISCO 222), and only 11.4 % of Nursing and midwifery associate professionals (ISCO 322), report the same. Notice that the EU LFS module on job skills does not capture other aspects of job quality that are critical in this sector, such as working time or high workload.

Jobs in the healthcare sector have somewhat lower than average cognitive task indices, which measure reading technical documents and performing complex calculations. However, there is a higher-than-average communication task share for the main occupational groups, which reflects both the extent of communication within the organisations (that is, between healthcare providers) and outside the organisation (that is, between healthcare providers and patients).

The use of digital devices at work by many health and care workers is much lower than the EU's and the sectoral average (Table 13, Eurofound, 2023a), with the exception of medical doctors and medical and pharmaceutical technicians.

Relevance of the task profiles for addressing the skills and labour shortages in the sector

The very high levels of manual (arduous) work and high routinisation in nursing occupations suggest that the designing of jobs and adjustments to the employment and working conditions in several core occupations of the sector could include improving the workload management, in ways that help improve individual autonomy whenever possible. Technological development, for example in the field of robotics, may also be directed at reducing the physical effort required by healthcare workers. The importance of communication tasks for many healthcare occupations shows that language training will likely remain one of key areas for integrating the migrant workforce within the sector.

There also needs to be careful consideration of the adoption of digital devices in the health and social care sector. On the one hand, digital technologies like telemedicine and electronic medical records have the potential to improve the quality of care for patients, by improving access to healthcare or in enabling independent living. On the other hand, the adoption of digital technologies by healthcare professionals should be implemented so as not to increase even further the high level of routine and low level of autonomy experienced by many workers in the sector. Merely digitising paper-based bureaucracy does not necessarily improve standards of care for patients or working conditions for healthcare workers.

In general, the experience of the COVID-19 pandemic has shown the need to reassess the crisis preparedness of the healthcare sector, not just in the case of public-health crises like pandemics, but also in terms of facing natural disasters or military threats.

Cognitive tasks and skill utilisation

The skills policy of the EU is primarily concerned with the supply of skills, aiming to ensure that the EU workforce has an adequate number of qualified workers. In its communication for the union of skills, the Commission highlights the scale of skill shortages and gaps (8), including concerns about the low and declining levels of literacy, numeracy and digital skills in education shown in the OECD Programme for International Student Assessment survey (9). Similarly, the European skills agenda set a target to raise the share of adults with at least basic digital skills, from 55 % in 2023 to 70 % in 2025 (10). The ability to read, calculate and use digital devices are frequently used as learning outcomes in compulsory and vocational education, and are considered key for employability because, as so-called ‘foundation skills’, they are considered key to acquiring other competencies. Given the importance of literacy, numeracy and digital skills in the policy debate surrounding employability, one would expect that their corresponding tasks (reading, writing, using digital devices) are important in many jobs, especially in office-based and so-called ‘high-skilled’ occupations, that make up an increasing share of EU employment. We may therefore ask to what extent is this really the case in the modern workplaces of developed EU economies?

The evidence from the EU LFS module on job skills is mixed. One of the advantages of the task-based approach used for the 2022 EU LFS module is that it asks respondents to estimate the frequency of various tasks in their jobs, as opposed to assessing the skill levels of respondents relative to an arbitrary academic standard. This allows us to gauge the importance of two key cognitive tasks – reading ‘work-related manuals and technical documents’ and ‘doing relatively complex calculations’ – as well as the use of digital devices across different occupations and in relation to the respondent’s educational attainment. The wording of questions is similar to those covered in the Survey of Adult Skills (PIAAC).

The ability to read, calculate and use digital devices are considered ‘basic skills’. The EU LFS module only measures these three tasks, which cannot cover the variety and complexity of tasks in modern workplaces. By comparison, the US O*Net database lists over 19 000 occupation-specific task statements, and the skills pillar of ESCO includes nearly 14 000 different skills. However, it is hard to imagine that professional upskilling and reskilling can occur without workers reading training material, notwithstanding the importance of informal and non-verbal forms of learning.

We should note that in principle there is a difference between how important a skill is in a given job, and how frequently the related task is performed. However, the relative or absolute importance is harder to measure objectively, and frequency is a useful proxy (11). It is also important to remember that respondents to the EU LFS module were able to respond that they carried out multiple tasks ‘All or most of the working time’, as no constraints were implemented across different answers.

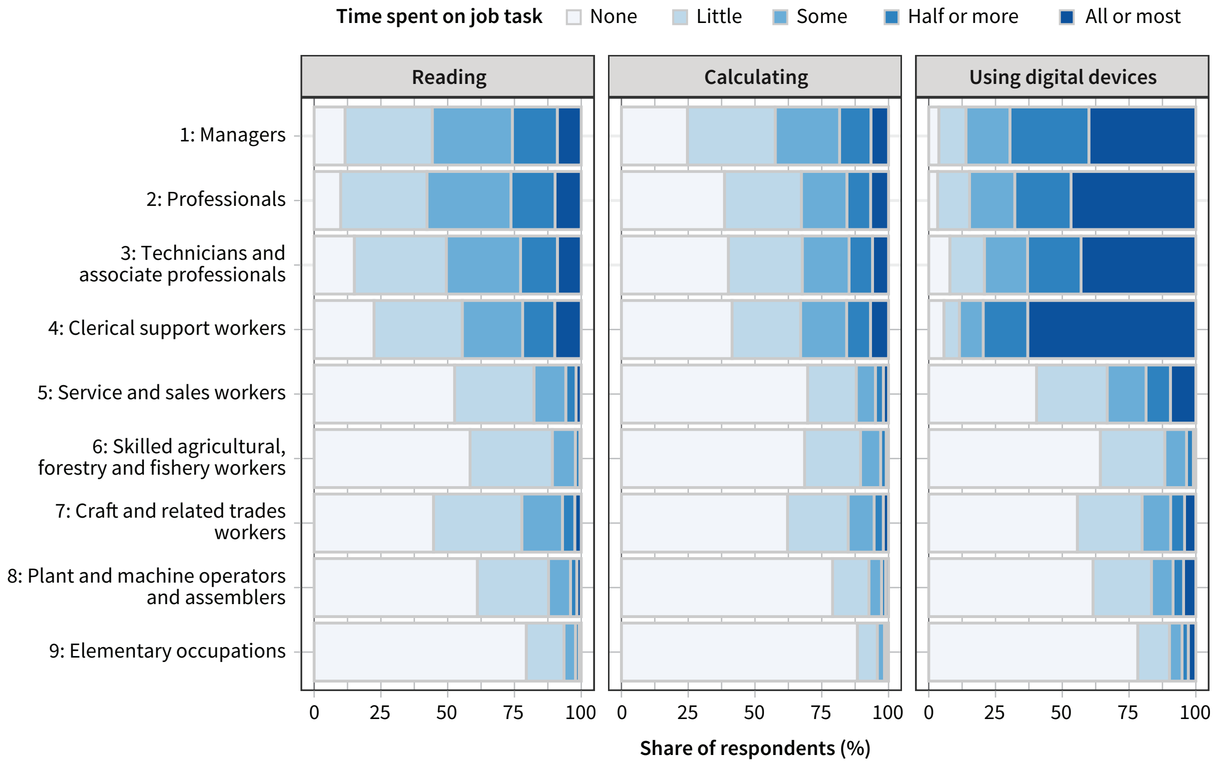
(8) Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions – The Union of Skills, COM(2025) 90 final of 5 March 2025, https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52025DC0090.

(9) European Commission: Directorate-General for Education, Youth, Sport and Culture, The twin challenge of equity and excellence in basic skills in the EU – An EU comparative analysis of the PISA 2022 results, Publications Office of the European Union, 2024, https://data.europa.eu/doi/10.2766/881521.

(10) European Commission, ‘European Skills Agenda’, European Commission website, https://employment-social-affairs.ec.europa.eu/policies-and-activities/skills-and-qualifications/european-skills-agenda_en.

(11) The Indagine Campionaria delle Professioni replicates the O*Net questionnaire in a survey of jobholders, and independently measures both frequency and importance for many task descriptors. Examining the responses, I have observed that the two dimensions are very highly correlated, at over 95 %. This suggests that survey respondents do not really distinguish between the concepts of ‘frequency’ and ‘importance’ of tasks.

Figure 14: Time spent on cognitive tasks, by occupation



Source: *2022 EU LFS module on job skills.*

The frequency of cognitive and digital tasks follows the ISCO occupational hierarchy: on one side are Managers, Professionals, Technicians and associate professionals, (ISCO 1–3, which collectively make up 'high-skilled occupations' in the ILO definition), and Clerical support workers (ISCO 4). In these occupations, around half of respondents say that they spend at least some of their working time reading, at least a third of them say they spend a similar time calculating and 80 % of them say they use digital devices at a similar rate. In the other group, which includes a range of occupations from Service and sales workers (ISCO 5) to Elementary occupations (ISCO 9), a majority of them say their job never involves reading, calculating or using digital devices – except for Service and sales workers, where 40 % never use digital devices.

The absolute task intensity remains concerningly low, even among highly educated workers. As shown in the table below, a majority of workers with a lower or upper secondary education (77 % and 66 %, respectively), and a sizeable minority of those with a tertiary education (44 %) report that their work involves reading 'Little to none of the working time'. Likewise, across all education levels, a majority of respondents report that their work involves calculating little to no of the working time: 80 % of those with a lower secondary education down to 63 % of those with a third-level education. By comparison, low use of digital devices is more common among respondents with a low-to-medium education level (72 % and 52 %, respectively), but rare among those with a tertiary education (only 18 % report little to none of the working time spent on using digital devices).

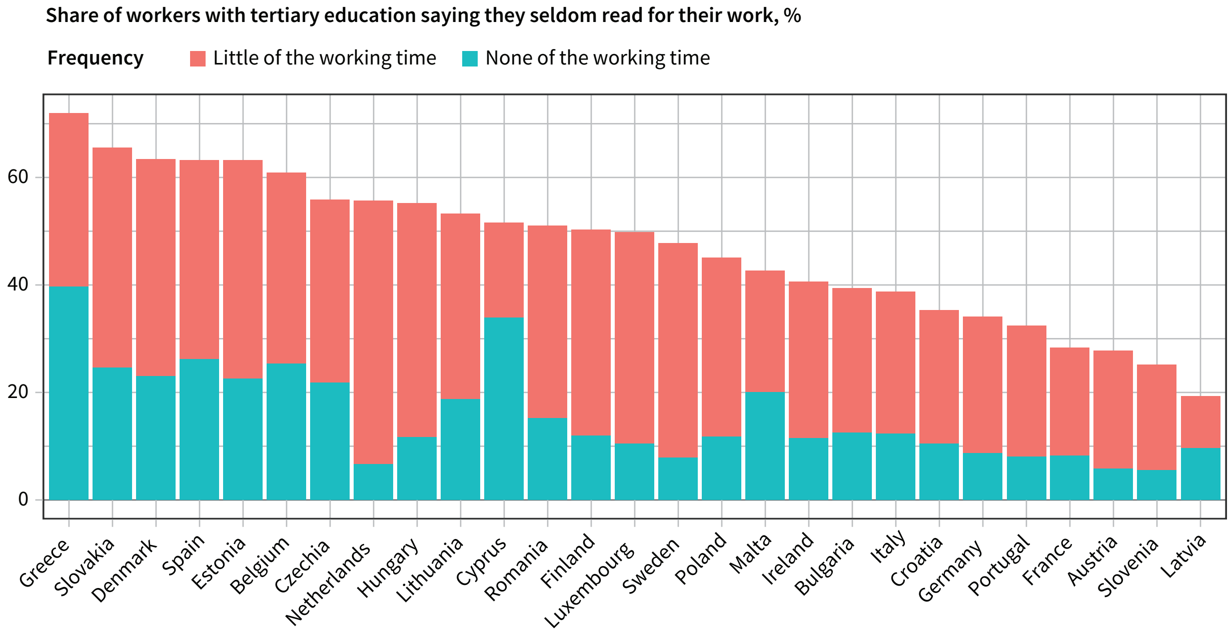
Table 14: Share of respondents doing few cognitive or digital tasks, by education level

	International Standard Classification of EducationManual		
	Low: Lower secondary	Medium: Upper secondary	High: Third level
Reading 'Little to none of the working time'	77 %	66 %	44 %
Calculating 'Little to none of the working time'	80 %	75 %	63 %
Using digital devices 'Little to none of the working time'	72 %	52 %	18 %

Interestingly, the degree of skills underusage varies significantly by Member State. Figure 15 reports Member State-level shares of workers with a tertiary degree who seldom read for their work. In Greece, Slovakia and Denmark, more than 60 % of highly educated workers read little to none of the working time, while in Austria, Slovenia and Latvia only 20 % to 30 % of them do.

These figures suggest that skill underutilisation – a form of skill mismatch – may be an equally pressing issue as skill shortages. The extent to which highly educated workers do not use basic literacy also varies substantially by Member State, including more than half of workers in Greece, Slovakia, Denmark, Spain, Estonia and Belgium.

Figure 15: Literacy underuse by Member State



4 Discussion and conclusions

The analysis of job tasks is one of the main tools for understanding labour market dynamics. As demonstrated in this paper, it can help explain recent structural changes in the labour market. Tasks are discrete units of labour in a production process – what people do at work – and relate to skills. The differences in tasks between occupations have been suggested as explanations for labour market trends, including the polarisation of employment and wages, whether jobs can be automated by machines, offshored or can be done from home.

Research on tasks for the EU – to which Eurofound has contributed since 2016 – used to be hampered by a lack of large, comparable cross-Member State data that cover job tasks in sufficient detail, therefore the implementation of the 2022 EU LFS module on job skills is an important development in addressing this gap. This paper presents new evidence using microdata from this module.

The analysis showed the variation of task profiles between Member States even for the same occupation, as well as by gender and along structural characteristics like sector and firm size. The paper also adds to the evidence base on labour and skills shortages, by comparing occupations experiencing shortages to those that are not, not just in terms of manual, cognitive and digital task content – and hence, skill levels – but also in terms of autonomy and routine, which relate to working conditions. Finally, the analysis revealed new evidence on the (under)use of basic skills like literacy in the workplace.

The paper developed six aggregate task indices using the 11 questions from the module: manual tasks (frequency of strength and dexterity in the job), cognitive tasks (reading, calculating), communication tasks (communicating with people inside and outside the organisation, and providing guidance and training) and using digital devices. These are measures of task content – how much the job entails working with physical objects, information or people – and relate to different types of skills. Another two task indices measure the effects of work organisation as it relates to job quality and working conditions: the degree of perceived autonomy (in the order and content of tasks) and routine (the degree to which job is standardised and repetitive). These task indices are intended as a minimal set of task descriptors that can be applied to any occupation, rather than a detailed task dictionary listing the tasks specific to each detailed occupation.

Key findings

As expected, the task indices vary most clearly by occupation groups: 'high-skilled' occupations including professional and managerial ones perform more cognitive tasks, fewer manual tasks and spend more than half their time using digital devices, compared to other occupations. They also enjoy higher autonomy, but, surprisingly, the level of routine is fairly constant between occupations. Higher levels of digital and cognitive tasks are correlated with higher income, as is autonomy.

There are marked **gender differences** in tasks, even accounting for different occupational distribution: women report around 13 % less autonomy and 5 % more routine, in relative terms, compared to men. These differences indicate that work organisation, which determines autonomy and routine, tends to adversely affect women on average.

Task profiles vary significantly by the **size of the firm**: jobs in larger firms tends to be more cognitive, less manual and much more digital than in smaller firms, while providing marginally more autonomy. Close to 40 % of employees in businesses with 10 or fewer workers report never using digital devices on the job, whereas this figure drops to just 15 % among those employed in large enterprises with 250 or more staff. The limited uptake of ICT in small and medium-sized enterprises across the EU is a well-recognised issue and has raised concerns among policymakers.

There is a substantial **variation in tasks between Member States**, even for the same job. The largest differences are in the indices for **digital**, **autonomy** and **routine**, which are far greater than what can be explained by Member States having a different mix of occupations. For example, Sweden has among the highest use of digital devices and Romania the lowest. This is not just because they employ different rates of conventionally digital occupations: software developers account for 5.1 % of Sweden's workforce, compared to 1.2 % in Romania. Much of the difference comes down to using digital devices in every other job: in Sweden, 60 % of nurses use digital devices at least half the working time, while in Romania only 12 % do. These differences highlight the crucial role of **work organisation** in shaping the way people work, **beyond the skills of individual workers**. The use of digital devices by clerks or nurses, for instance, is less about their abilities and more about whether their workplaces incorporate such technologies. Similarly, variations in national institutions and cultures probably influence how work is structured, leading to differing levels of autonomy and routine across Member States.

Changing task composition in the EU economy

Task data also shines a new light on the extent of **structural change** in the EU labour market. Over the past decade, employment in the EU has increased in cognitive and digital occupations. Specifically, there has been growth in jobs that involve relatively high levels of cognitive tasks, such as reading and calculating, frequent use of digital devices, enhanced communication, greater autonomy and less routine work. In contrast, employment levels have largely remained constant in occupations that are more manual in nature. These jobs typically involve low cognitive tasks, minimal communication or use of digital devices, and are characterised by low autonomy or high levels of routine. Notably, in 2023, employment in highly digital occupations – those that make above-average use of digital devices – has surpassed that in low-digital occupations for the first time. This shift underscores the increasing importance of digital skills for the entire workforce. If current trends continue, employment in occupations with relatively high cognitive task content is poised to overtake those with low task content soon. This transition reflects a broader shift towards more cognitively demanding roles in the labour market.

Implications for skills and labour shortages

These trends expand on previous findings relating to the nature of **skill shortages**. On average, occupations experiencing the most acute shortages tend to involve more manual tasks and lower use of digital devices compared to other jobs. Moreover, there are no significant aggregate differences in autonomy or routine between shortage and non-shortage occupations. This overall pattern may obscure important exceptions – such as in the healthcare sector – where acute shortages of qualified workers or difficult working conditions do contribute to recruitment challenges.

These findings may inform the **quality jobs roadmap**, by showing the importance of combining measures of task content (related to skills) with measures of job organisations (related to job quality).

Rather than skill shortages, the data suggests that **skill underutilisation** is a problem. A significant proportion of employees, including many with higher education qualifications, report limited engagement in tasks such as reading and calculating. For example, 44 % of workers with a tertiary education indicate they spend little or no time reading during their workday, while 63 % say the same about performing calculations. The figures vary substantially by Member State: in Greece, Slovakia, Denmark, Spain, Estonia and Belgium, more than half of workers with a tertiary education say that their job involves little to no reading.

Future research

The EU LFS data on job tasks can have several additional applications beyond the scope of this paper. The first is to provide new a Member State-level estimate on the share of teleworkable employment (Eurofound, in progress). Previous estimates were based on Italian task-based data from 2012, and did not vary by Member State. As this paper revealed, there are sizeable task differences between Member States and the task profile of occupations may have changed somewhat since teleworkability was estimated based on 2012 data.

Another application concerns the variable on cognitive tasks – reading and calculating – which overlap somewhat with measurements in the PIAAC survey and could be analysed in greater detail.

Finally, future research could consider expanding the analysis of task difference between firms of different sizes, to explicitly control for sectoral and occupational differences.

In conclusion, despite its limited scope, the 2022 EU LFS module on job skills provides a valuable addition to the analysis of EU labour markets from the perspective of job tasks.

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Annexes

Annex 1: The EU LFS module on job skills – structure and sample size

Table 15: Concepts, questionnaire and derived variables in the 2022 EU LFS module on job skills

<table>
<tr><th colspan="2">Concepts – from Eurofound-JRC task framework</th><th colspan="3">Questions in EU LFS ad hoc module on job skills</th><th colspan="2">Variables derived for analysis</th></tr>
<tr><th>Task pillar</th><th>Dimensions (task framework name)</th><th>Identifier</th><th>Description</th><th>Values</th><th>Variable (abbreviation)</th><th>Values</th></tr>
<tr><td rowspan="8">Content</td><td rowspan="2">Manual</td><td>PHYSICAL</td><td>Time spent on doing hard physical work in main or last job</td><td rowspan="8">Frequency scale:
1. All or most of the working time
2. Half of the working time or slightly more
3. Some of the working time
4. Little of the working time
5. None of the working time</td><td>Strength</td><td rowspan="8">Numeric encoding
1. 1
2. 0.5
3. 0.25
4. 0.1
5. 0</td></tr>
<tr><td>DEXTERITY</td><td>Time spent on tasks involving finger dexterity in main or last job</td><td>Dexterity</td></tr>
<tr><td rowspan="2">Cognitive (‘Intellectual tasks’)</td><td>READING</td><td>Time spent on reading work-related manuals and technical documents in main or last job</td><td>Reading</td></tr>
<tr><td>CALCULATE</td><td>Time spent on doing relatively complex calculations in main or last job</td><td>Calculating</td></tr>
<tr><td rowspan="4">Social</td><td>GUIDANCE</td><td>Time spent on advising, training or teaching other people in main or last job</td><td>Providing training (training)</td></tr>
<tr><td>COMMEXT</td><td>Time spent on interacting with people from outside the enterprise or organisation in main or last job</td><td>Internal communication (commint)</td></tr>
<tr><td>COMMINT</td><td>Time spent on interacting with people from the same enterprise or organisation in main or last job</td><td>External communication (commext)</td></tr>
<tr></tr>
<tr><td>Methods and tools</td><td>Digital tools (Information processing)</td><td>DIGITAL</td><td>Time spent on working on digital devices in main or last job</td><td>Frequency scale:
1. All or most of the working time
2. Half of the working time or slightly more
3. Some of the working time
4. Little of the working time
5. None of the working time</td><td></td><td></td></tr>
</table>

Concepts – from Eurofound-JRC task framework		Questions in EU LFS ad hoc module on job skills			Variables derived for analysis	
Task pillar	**Dimensions (task framework name)**	**Identifier**	**Description**	**Values**	**Variable (abbreviation)**	**Values**
Methods and tools	Autonomy	JOBAUTON	Degree of autonomy for tasks in main or last job	Bivariate size scale: 1. Large for both order and content 2. Large for order and some on content 3. Large for order and little (or no) on content 4. Some on order and large on content 5. Some autonomy on both order and content 6. Some on order and little (or no) on content 7. Little (or no) on order and large on content 8. Little (or no) on order and some on content 9. Little (or no) on both order and content	Autonomy in order (autorder) Autonomy in content (autcont) Job autonomy (autonomy) derived as: min (autorder, autcont)	Numeric encoding 1. Large = 1 2. Some = 0.5 3. Little (or no) = 0
	Routine	REPETITIVE	Repetitiveness of tasks in main or last job	Extent scale: 1. To a very large extent 2. To a large extent 3. To some extent 4. To little extent 5. To no extent	Repetitiveness (repetitive)	Numeric encoding 1. 1 2. 0.5 3. 0.25 4. 0.1 5. 0
		PROCEDURE	Tasks precisely described by strict procedures in main or last job		Standardisation (standard)	

Note: *The table shows the structure and concepts from the Eurofound–JRC task framework (left columns), the full wording of questions and responses in the EU LFS ad hoc module on job skills, with the identifiers as provided in the EU LFS (central columns) and the variables derived from these questions, as used in this paper (right columns).*

Sample size

Table 16 shows the sample size of the 2022 ad hoc module on job skills (AHM), which is described in this paper, in relation to the sample of the EU LFS. The EU LFS is composed of a quarterly panel and a smaller yearly panel of respondents.

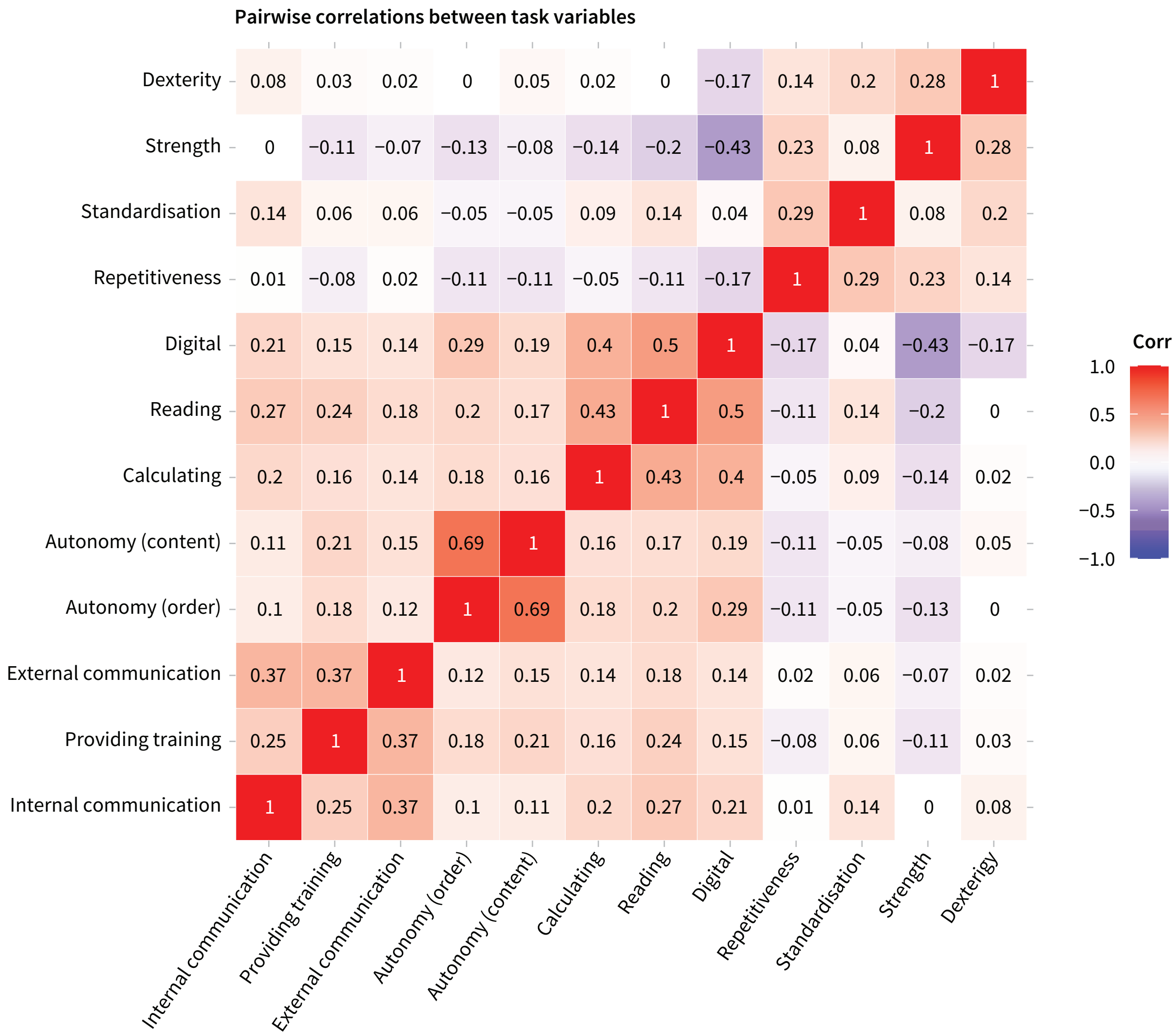
Table 16: Sample size of EU LFS and ad hoc module on job skills

Member State	EU LFS yearly sample	AHM target	AHM administered	AHM respondents	
	N	N	N	N	(%)
Austria	172 668	97 651	19 122	19 122	20
Belgium	37 714	17 857	17 857	17 847	100
Bulgaria	31 188	14 975	14 975	14 939	100
Croatia	41 396	17 053	4 100	4 082	24
Cyprus	37 106	19 623	6 434	6 434	33
Czechia	38 211	18 536	18 536	16 479	89
Denmark	95 528	42 543	11 318	10 728	25
Estonia	26 401	14 339	7 243	7 206	50
Finland	15 484	10 840	10 840	10 470	97
France	68 110	31 794	31 794	30 508	96
Germany	202 656	111 355	62 603	28 219	25
Greece	29 263	11 696	11 696	11 181	96
Hungary	218 550	105 517	16 054	15 751	15
Ireland	22 270	10 519	10 519	6 952	66
Italy	512 873	211 519	49 289	46 596	22
Latvia	9 199	4 825	4 825	4 561	95
Lithuania	51 465	29 135	7 353	7 353	25
Luxembourg	8 299	4 939	4 939	4 777	97
Malta	10 988	5 374	5 374	5 374	100
Netherlands	65 093	51 197	51 197	47 010	92
Poland	262 313	120 703	25 798	23 777	20
Portugal	32 274	15 930	15 9329	13 958	88
Romania	213 412	88 789	22 140	22 129	25
Slovakia	160 102	75 766	15 176	14 898	20
Slovenia	70 448	35 074	8 538	8 538	24
Spain	84 727	40 534	40 534	35 296	87
Sweden	89 574	67 200	11 418	11 158	17
EU-27 total	**2 607 312**	**1 275 283**	**505 601**	**445 343**	**35**

Annex 2: Task indices

Correlation between variables in the LFS questionnaire

Figure 16: Correlation between variables from the LFS questionnaire



Task indices by Member State

Table 17: Average task indices by Member State

	Manual	Cognitive	Communication	Digital	Autonomy	Routine
EU average	**0.205**	**0.138**	**0.250**	**0.360**	**0.377**	**0.365**
Austria	0.238	0.308	0.419	0.477	0.408	0.461
Belgium	0.177	0.118	0.271	0.383	0.396	0.341
Bulgaria	0.172	0.103	0.196	0.215	0.222	0.406
Croatia	0.180	0.119	0.279	0.315	0.301	0.458
Cyprus	0.175	0.103	0.324	0.379	0.098	0.486
Czechia	0.147	0.098	0.226	0.326	0.272	0.393
Denmark	0.142	0.107	0.305	0.404	0.457	0.316
Estonia	0.203	0.122	0.287	0.394	0.373	0.421
Finland	0.184	0.127	0.296	0.436	0.477	0.384
France	0.274	0.226	0.428	0.434	0.442	0.349
Germany	0.139	0.106	0.119	0.327	0.268	0.250
Greece	0.233	0.069	0.162	0.229	0.282	0.370
Hungary	0.212	0.122	0.183	0.290	0.413	0.539
Ireland	0.184	0.128	0.272	0.344	0.298	0.367
Italy	0.295	0.139	0.267	0.342	0.461	0.366
Latvia	0.211	0.204	0.178	0.364	0.402	0.368
Lithuania	0.201	0.135	0.273	0.342	0.520	0.502
Luxembourg	0.120	0.198	0.287	0.552	0.582	0.376
Malta	0.208	0.202	0.468	0.462	0.420	0.475
Netherlands	0.166	0.148	0.174	0.515	0.492	0.393
Poland	0.189	0.120	0.208	0.308	0.357	0.371
Portugal	0.202	0.142	0.262	0.347	0.473	0.427
Romania	0.161	0.088	0.160	0.191	0.224	0.395
Slovakia	0.184	0.071	0.153	0.267	0.180	0.527
Slovenia	0.209	0.182	0.291	0.431	0.308	0.481
Spain	0.230	0.117	0.328	0.377	0.449	0.439
Sweden	0.145	0.172	0.284	0.542	0.497	0.358

Note: *Task index can vary from 0 (low) to 1 (high).*
Source: *Elaboration from 2022 EU LFS module on job skills.*

Task indices by NACE sections

Table 18: Task indices by NACE one-digit section, 2022, EU-27

Section NACE Rev2, one-digit	Manual	Cognitive	Communication	Digital	Autonomy	Routine
Agriculture, forestry and fishing	0.33	0.06	0.12	0.08	0.35	0.51
Mining and quarrying	0.26	0.11	0.15	0.24	0.37	0.26
Manufacturing	0.25	0.13	0.17	0.31	0.39	0.31
Electricity, gas, steam and air conditioning supply	0.14	0.20	0.23	0.55	0.36	0.39
Water supply; sewerage, waste management and remediation activities	0.22	0.11	0.18	0.29	0.38	0.29
Construction	0.36	0.13	0.19	0.19	0.37	0.39
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.20	0.13	0.29	0.35	0.35	0.38
Transportation and storage	0.18	0.11	0.20	0.32	0.41	0.26
Accommodation and food service activities	0.24	0.07	0.28	0.16	0.41	0.35
Information and communication	0.06	0.23	0.25	0.85	0.28	0.50
Financial and insurance activities	0.04	0.28	0.31	0.81	0.35	0.44
Real estate activities	0.08	0.21	0.28	0.56	0.30	0.54
Professional, scientific and technical activities	0.08	0.28	0.26	0.74	0.32	0.54
Administrative and support service activities	0.20	0.10	0.20	0.32	0.36	0.34
Public administration and defence; compulsory social security	0.10	0.19	0.26	0.57	0.37	0.36
Education	0.11	0.16	0.42	0.36	0.31	0.46
Human health and social work activities	0.25	0.11	0.30	0.29	0.43	0.36
Arts, entertainment and recreation	0.18	0.12	0.30	0.38	0.32	0.48
Other service activities	0.28	0.10	0.26	0.29	0.35	0.47
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0.24	0.01	0.11	0.02	0.30	0.51
Activities of extraterritorial organisations and bodies	0.04	0.24	0.26	0.73	0.33	0.43

Note: *Task index can vary from 0 (low) to 1 (high).*
Source: *Elaboration of 2022 EU LFS module on job skills.*

Sector grouping

Table 19: Grouping of sectors of economic activity and employment numbers (age 15–65), EU-27

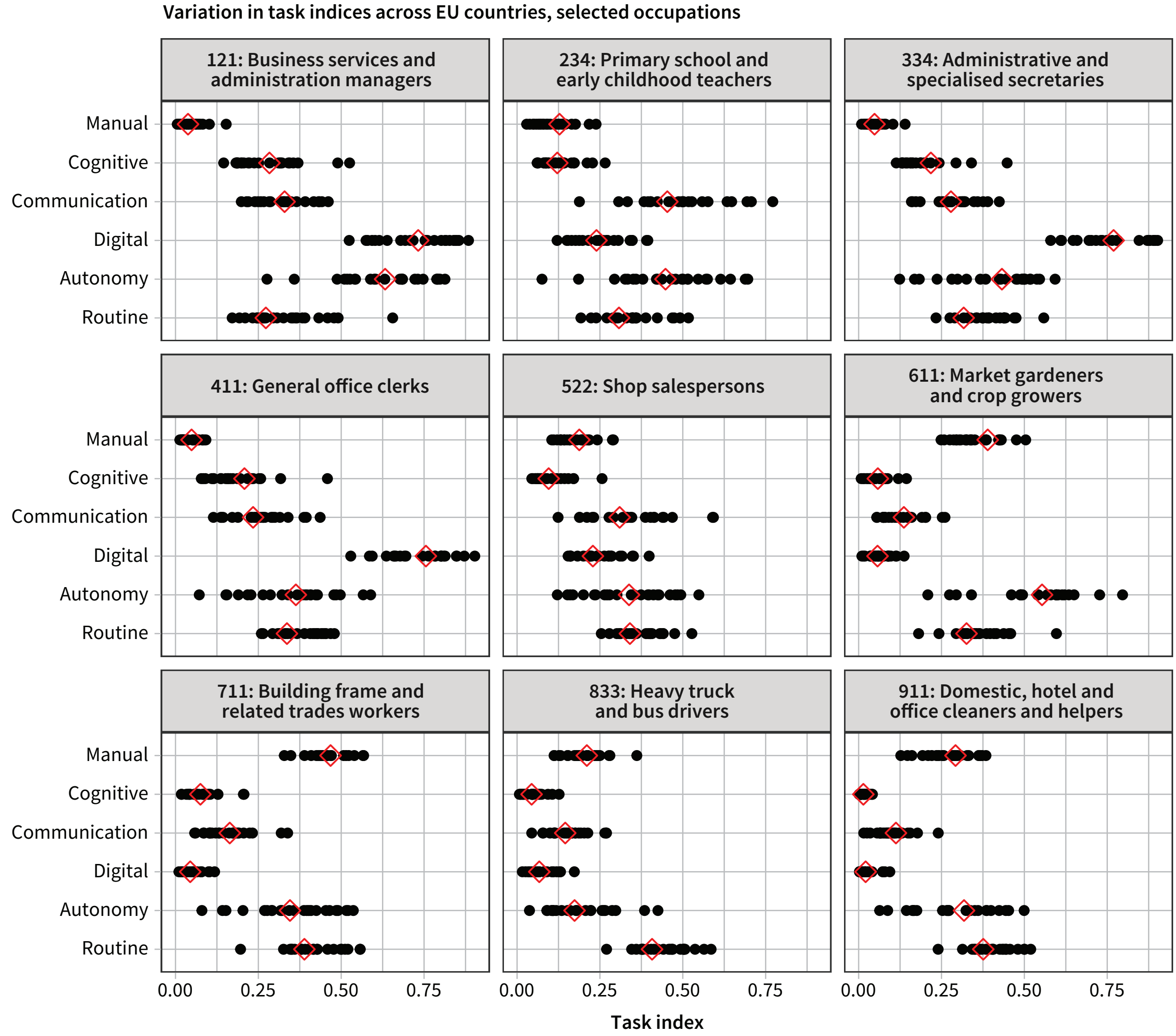
Sector group	NACE section	Employment (thousand)	
		2011	2022
Agriculture/extractive	A: Agriculture, forestry and fishing	9 368.1	7 010.6
	B: Mining and quarrying	708.7	538.5
Construction	F: Construction	13 466.0	13 554.8
Manufacturing/utilities	C: Manufacturing	30 14.0	31 577.6
	D: Electricity, gas, steam and air conditioning	1 509.9	1 518.8
	E: Water supply; sewerage, waste management	1 375.7	1 645.0
Mainly public services	O: Public administration and defence	13 386.4	13 830.6
	P: Education	12 832.9	14 593.5
	Q: Human health and social work activities	18 654.5	21 845.8
	U: Activities of extraterritorial organisations and bodies	151.5	158.9
Mainly private services	G: Wholesale and retail trade; repair of motor vehicles	25 752.6	26 767.3
	H: Transportation and storage	9 443.3	10 389.3
	I: Accommodation and food service activities	8 016.8	8 947.2
	J: Information and communication	5 110.2	7 383.1
	K: Financial and insurance activities	5 272.1	5 364.3
	L: Real estate activities	1 320.6	1 684.2
	M: Professional, scientific and technical activities	8 778.0	11 351.7
	N: Administrative and support service activities	7 097.2	8 256.2
	R: Arts, entertainment and recreation	2 752.2	3 221.2
	S: Other service activities	4 416.1	5 202.3
	T: Activities of households as employers	2 469.7	1 812.8

Note: *Sector groupings used in Eurofound (2025).*
Source: *EU LFS, 2011 and 2022.*

Task indices for selected occupations across Member States

Figure 17 shows selected occupation groups at ISCO three-digit level (also known as 'minor group') – the most detailed occupational grouping available in the EU LFS microdata – chosen to be among the largest for each ISCO one-digit 'major group'. The occupations run the spectrum from managerial occupations to elementary ones, namely:
121: Business services and administration managers, 234: Primary school and early childhood teachers,
334: Administrative and specialised secretaries, 411: General office clerks, 522: Shop salespersons, 611: Market gardeners and crop growers, 711: Building frame and related trades workers, 833: Heavy truck and bus drivers and 911: Domestic, hotel and office cleaners and helpers.

Figure 17: Variation in task indices



Note: *Each panel represents the how the average task indices vary for selected occupations across 24 Member States. Each dot represents one Member State, where the horizontal axis shows the average value of the task index, which can range 0 (lowest possible value) to 1 (highest possible value). The red diamonds denote the EU average. Member States include the EU-27, except for Bulgaria, Malta and Slovenia, which do not report occupations at the ISCO three-digit levels.*
Source: *2022 EU LFS ad hoc module on job skills.*

Occupation task rankings

The Table 20 shows ISCO three-digit occupations ranked according to each aggregate task index: manual, cognitive, communication, digital, autonomy and routine.

Table 20: Ranking of occupations by task indices

	Value	ISCO occupation
Manual		
5 Highest	0.489	712: Building finishers and related trades workers
	0.473	622: Fishery workers, hunters and trappers
	0.468	711: Building frame and related trades workers
	0.462	514: Hairdressers, beauticians and related workers
	0.460	713: Painters, building structure cleaners and related trades workers
Median	0.212	312: Mining, manufacturing and construction supervisors
5 Lowest	0.038	121: Business services and administration managers
	0.036	242: Administration professionals
	0.031	241: Finance professionals
	0.0.27	261: Legal professionals
	0.025	212: Mathematicians, actuaries and statisticians
Cognitive		
5 Highest	0.423	212: Mathematicians, actuaries and statisticians
	0.367	241: Finance professionals
	0.347	331: Financial and mathematical associate professionals
	0.322	211: Physical and earth science professionals
	0.309	431: Numerical clerks
Median	0.122	224: Paramedical practitioners
5 Lowest	0.021	961: Refuse workers
	0.018	921: Agricultural, forestry and fishery labourers
	0.014	911: Domestic, hotel and office cleaners and helpers
	0.009	631: Subsistence crop farmers
	0.000	634: Subsistence fishers, hunters, trappers and gatherers
Communication		
5 Highest	0.522	233: Secondary education teachers
	0.502	232: Vocational education teachers
	0.462	235: Other teaching professionals
	0.453	234: Primary school and early childhood teachers
	0.437	342: Sports and fitness workers
Median	0.239	252: Database and network professionals
5 Lowest	0.088	632: Subsistence livestock farmers
	0.085	633: Subsistence mixed crop and livestock farmers
	0.084	613: Mixed crop and animal producers
	0.081	634: Subsistence fishers, hunters, trappers and gatherers
	0.074	631: Subsistence crop farmers

	Value	ISCO occupation
Digital		
5 Highest	0.924	212: Mathematicians, actuaries and statisticians
	0.923	251: Software and applications developers and analysts
	0.913	252: Database and network professionals
	0.882	133: Information and communications technology services managers
	0.864	351: Information and communications technology operations and user support technicians
Median	0.280	131: Production managers in agriculture, forestry and fisheries
5 Lowest	0.031	961: Refuse workers
	0.025	931: Mining and construction labourers
	0.021	911: Domestic, hotel and office cleaners and helpers
	0.019	921: Agricultural, forestry and fishery labourers
	0.000	634: Subsistence fishers, hunters, trappers and gatherers
Autonomy		
5 Highest	0.823	323: Traditional and complementary medicine associate professionals
	0.732	143: Other services managers
	0.719	633: Subsistence mixed crop and livestock farmers
	0.706	133: Information and communications technology services managers
	0.688	133: Information and communications technology services managers
Median	0.381	431: Numerical clerks
5 Lowest	0.142	523: Cashiers and ticket clerks
	0.128	831: Locomotive engine drivers and related workers
	0.123	818: Other stationary plant and machine operators
	0.119	634: Subsistence fishers, hunters, trappers and gatherers
	0.102	932: Manufacturing labourers
Routine		
5 Highest	0.565	831: Locomotive engine drivers and related workers
	0.545	315: Ship and aircraft controllers and technicians
	0.532	222: Nursing and midwifery professionals
	0.531	751: Food processing and related trades workers
	0.529	816: Food and related products machine operators
Median	0.377	131: Production managers in agriculture, forestry and fisheries
5 Lowest	0.237	243: Sales, marketing and public relations professionals
	0.237	212: Mathematicians, actuaries and statisticians
	0.233	223: Traditional and complementary medicine professionals
	0.230	122: Sales, marketing and development managers
	0.223	133: Information and communications technology services managers

Source: *2022 EU LFS.*

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This paper provides new evidence on the types of tasks that are carried out at work in the European Union (EU). It highlights the changes in the recent structural composition of employment in the EU-27, and it analyses the data on tasks in the context of labour and skills shortages and skill utilisation. Modern employment research relies on the theory and data of job tasks – units of work within the production process that are bundled into jobs and may require different skills. The task approach is used in the related literature to study structural employment trends and the impact of new technologies on work and to make predictions on the share of the labour force exposed to automation and offshoring or that is capable of telework.

Existing data on job tasks in the EU used to be limited to a few national surveys or ad hoc data collections. This prevented comparisons between EU Member States or the assessment of whether the same occupations had the same task profiles in every Member State. This paper presents microdata from the 2022 module of the EU Labour Force Survey (EU LFS) on job skills, which covered 11 key task types on a large scale across the EU, for nearly half a million respondents. The types of tasks surveyed address the content of work (manual, cognitive and communication), which relates to the different types of skills, the methods of work (autonomy and standardisation) and the use of digital devices. The results show substantial variation in the task profiles between occupation, gender, income level, firm size and Member State – even for the same occupation. The paper presents applications of the data to analyse labour shortages and to estimate skill (under)use in the EU.

The European Foundation for the Improvement of Living and Working Conditions (Eurofound) is a tripartite European Union Agency established in 1975. Its role is to provide knowledge in the area of social, employment and work-related policies according to Regulation (EU) 2019/127.

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